

**Qualifying Exam: CAS MA 576.**  
Boston University, Spring 2009

**Question 3**

Let  $\{Y_1, \dots, Y_n\}$  Be a set of independent RVs with  $E(Y_i) = \mu_i$ ,  $var(Y_i) = \sigma^2 V(\mu_i)$ , And

$$V(\mu) = \mu(1 + \alpha\mu)$$

for some known constant  $\alpha$ .

- (a) Show that the quasi-likelihood (QL) for a single  $Y$  is

$$y \log \frac{\mu}{y} - \left( y + \frac{1}{\alpha} \right) \log \frac{(1 + \alpha\mu)}{(1 + \alpha y)}$$

Hint: Write down the Quasi Score  $U$ . Show that

$$\int \frac{y-t}{t(1+\alpha t)} = y \log(t) - \left( y + \frac{1}{\alpha} \right) \log(1 + \alpha t),$$

If you want you can use the identity

$$\frac{1}{t(1+\alpha t)} = \frac{1 + \alpha t - \alpha t}{t(1+\alpha t)} = \frac{1}{t} - \frac{\alpha}{1 + \alpha t}$$

- (b) Calculate the QL for  $\{Y_1, \dots, Y_n\}$  and derive the quasi-deviance (QD).
- (c) Write down the QD for  $\alpha = -1$ . What exponential family does the QD correspond to in this case?
- (d) Show that when  $\alpha = 0$ , the QD is the same as the deviance for Poisson distributed data.
- (e) Can you obtain the deviance under the normal distribution and gamma distribution as special cases of the above  $V(\mu)$ ? If yes for which values of  $\alpha$  would they correspond to. Otherwise propose a variance function  $V(\mu)$ , which may include Normal, Gamma, Binomial and Poisson as special cases. [You do not need to work out the QL/QD]

## Question 4

This question is based on the analysis of the following study:

The data are taken from a clinical trial of 59 epileptics, who were randomized to receive either the anti-epileptic drug progabide or a placebo. The data on each subject consist of a baseline count of the number of seizures over an eight-week period prior to treatment allocation, followed by counts in four two-week periods post-treatment.

| var  | Description  |
|------|--|
| y1   | counts of number of seizures in first two-week period after post-treatment                       |
| y2   | counts of number of seizures in second two-week period after post-treatment                      |
| y3   | counts of number of seizures in third two-week period after post-treatment                       |
| y4   | counts of number of seizures in fourth two-week period after post-treatment                      |
| trt  | whether received anti-epileptic drug progabide (trt=1) or placebo (trt=0)                        |
| base | baseline count of the number of seizures over an eight-week period prior to treatment allocation |
| age  | age of the subject   |

In this question we shall analyze a subset of data taken from a clinical trial of 59 epileptics, who were randomized to receive either the anti-epileptic drug progabide or a placebo. The data on each subject consist of a baseline count of the number of seizures over an eight-week period prior to treatment allocation, followed by counts in four two-week periods post-treatment.

The following few pages provides outputs from a range of Poisson models with and without overdispersion for modeling the number of seizures in the fourth two-week period of post-treatment (variable y4), in terms of the baseline count, age and treatment. Describe the steps for selecting the best model commenting specifically and justifying your choice for using

- Overdispersion Poisson vs Standard poisson regression.
- Inclusion and exclusion of interaction terms (2nd and 3rd order).
- Inclusion and exclusion of main effects.
- Model comparison based on “F” vs “Chisq” distribution.

Write down the statistical model that you finally choose and justify your choice.

## Description of Models

```

seiz.mult=glm(y4~ trt*base*age,data=seizure,family=poisson)
seiz.twoway=glm(y4~ trt*base+trt*age+age*base,data=seizure,family=poisson)
seiz.add=glm(y4~ trt+base+age,data=seizure,family=poisson)
seiz.base.trt=glm(y4~ base*trt,data=seizure,family=poisson)
seiz.onlybase=glm(y4~ base,data=seizure,family=poisson)

seiz.mult.overd=glm(y4~ trt*base*age,data=seizure,family=quasipoisson)
seiz.twoway.overd=glm(y4~ trt*base+trt*age+age*base,data=seizure,family=quasipoisson)
seiz.add.overd=glm(y4~ trt+base+age,data=seizure,family=quasipoisson)
seiz.base.trt.overd=glm(y4~ base*trt,data=seizure,family=quasipoisson)
seiz.onlybase.overd=glm(y4~ base,data=seizure,family=quasipoisson)

```

## Summary of Possion Glm Models

```

#####
> summary(seiz.mult)
Call:
glm(formula = y4 ~ trt * base * age, family = poisson, data = seizure)

Coefficients:
            Estimate Std. Error z value P(>|z|)
(Intercept)  1.3400322   0.7148376   1.875  0.0608 .
trt          -0.0243711   0.8832661  -0.028  0.9780
base         0.0072530   0.0157319   0.461  0.6448
age         -0.0027286   0.0240156  -0.114  0.9095
trt:base    -0.0160298   0.0194789  -0.823  0.4105
trt:age     -0.0209968   0.0309935  -0.677  0.4981
base:age     0.0004560   0.0005262   0.867  0.3862
trt:base:age 0.0009598   0.0007311   1.313  0.1893
-----
Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 134.77  on 51  degrees of freedom
AIC: 339.03

#####
> summary(seiz.twoway)

Call:
glm(formula = y4 ~ trt * base + trt * age + age * base, family = poisson,
    data = seizure)

Coefficients:
            Estimate Std. Error z value P(>|z|)
(Intercept)  1.9306546   0.5469775   3.530 0.000416 ***
trt          -0.9594936   0.5062628  -1.895 0.058060 .
base         -0.0077995   0.0108607  -0.718 0.472670
age         -0.0228912   0.0184028  -1.244 0.213538
trt:base     0.0091700   0.0035132   2.610 0.009050 **
trt:age      0.0137299   0.0154728   0.887 0.374888
base:age     0.0009635   0.0003608   2.670 0.007581 **
-----

Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 136.51  on 52  degrees of freedom
AIC: 338.76

```

```
#####  
> summary(seiz.add)
```

```
Call:  
glm(formula = y4 ~ trt + base + age, family = poisson, data = seizure)
```

```
Coefficients:  
            Estimate Std. Error z value P(>|z|)  
(Intercept)  0.728587   0.245920   2.963  0.00305 **  
trt          -0.278916   0.098866  -2.821  0.00479 **  
base         0.022153   0.001092  20.293 < 2e-16 ***  
age          0.015612   0.007159   2.181  0.02921 *
```

```
Null deviance: 473.79 on 58 degrees of freedom  
Residual deviance: 144.57 on 55 degrees of freedom  
AIC: 340.83
```

```
#####  
> summary(seiz.base.trt)
```

```
Call:  
glm(formula = y4 ~ base * trt, family = poisson, data = seizure)
```

```
Coefficients:  
            Estimate Std. Error z value P(>|z|)  
(Intercept)  1.2530157  0.1172758  10.684 <2e-16 ***  
base         0.0208717  0.0019112  10.920 <2e-16 ***  
trt         -0.3606720  0.1619755  -2.227  0.0260 *  
base:trt     0.0008258  0.0022749   0.363  0.7166
```

```
Null deviance: 473.79 on 58 degrees of freedom  
Residual deviance: 149.04 on 55 degrees of freedom  
AIC: 345.30
```

```
#####  
> summary(seiz.onlybase)
```

```
Call:  
glm(formula = y4 ~ base, family = poisson, data = seizure)
```

```
Coefficients:  
            Estimate Std. Error z value P(>|z|)  
(Intercept)  1.0987359  0.0770681  14.26 <2e-16 ***  
base         0.0208148  0.0009973  20.87 <2e-16 ***
```

```
Null deviance: 473.79 on 58 degrees of freedom  
Residual deviance: 159.40 on 57 degrees of freedom  
AIC: 351.66
```

## Summary of Poisson Glm Models using overdispersion

```

> summary(seiz.twoway.overd)
Call:
glm(formula = y4 ~ trt * base + trt * age + age * base, family = quasipoisson,
     data = seizure)

Coefficients:
            Estimate Std. Error t value P(>|t|)
(Intercept)  1.9306546  0.8579587   2.250  0.0287 *
trt          -0.9594936  0.7940958  -1.208  0.2324
base         -0.0077995  0.0170355  -0.458  0.6490
age          -0.0228912  0.0288657  -0.793  0.4314
trt:base      0.0091700  0.0055106   1.664  0.1021
trt:age       0.0137299  0.0242698   0.566  0.5740
base:age      0.0009635  0.0005660   1.702  0.0947 .
-----

(Dispersion parameter for quasipoisson family taken to be 2.460333)

Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 136.51  on 52  degrees of freedom
#####
> summary(seiz.add.overd)
Call:
glm(formula = y4 ~ trt + base + age, family = quasipoisson, data = seizure)

Coefficients:
            Estimate Std. Error t value P(>|t|)
(Intercept)  0.728587  0.383258   1.901  0.0625 .
trt          -0.278916  0.154080  -1.810  0.0757 .
base          0.022153  0.001701  13.021 <2e-16 ***
age           0.015612  0.011158   1.399  0.1673
-----

(Dispersion parameter for quasipoisson family taken to be 2.428819)

Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 144.57  on 55  degrees of freedom
#####
> summary(seiz.base.trt.overd)
Call:
glm(formula = y4 ~ base * trt, family = quasipoisson, data = seizure)

Coefficients:
            Estimate Std. Error t value P(>|t|)
(Intercept)  1.2530157  0.1876564   6.677 1.27e-08 ***
base          0.0208717  0.0030582   6.825 7.30e-09 ***
trt          -0.3606720  0.2591817  -1.392   0.170
base:trt      0.0008258  0.0036401   0.227   0.821
-----

(Dispersion parameter for quasipoisson family taken to be 2.560414)

Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 149.04  on 55  degrees of freedom
#####

```

```

> summary(seiz.onlybase.overd)

Call:
glm(formula = y4 ~ base, family = quasipoisson, data = seizure)

Coefficients:
              Estimate Std. Error t value P(>|t|)
(Intercept)  1.098736   0.124966   8.792 3.38e-12 ***
base         0.020815   0.001617  12.872 < 2e-16 ***
---

(Dispersion parameter for quasipoisson family taken to be 2.629268)

Null deviance: 473.79  on 58  degrees of freedom
Residual deviance: 159.40  on 57  degrees of freedom

```

### Comaprison of Possion Glm Models

```

#####
> anova(seiz.mult, seiz.twoway, seiz.add, seiz.onlybase, test="Chisq")
Analysis of Deviance Table

Model 1: y4 ~ trt * base * age
Model 2: y4 ~ trt * base + trt * age + age * base
Model 3: y4 ~ trt + base + age
Model 4: y4 ~ base
  Resid. Df Resid. Dev Df Deviance  P(>|Chi|)
1         51    134.770
2         52    136.507 -1    -1.737    0.187
3         55    144.569 -3    -8.062    0.045
4         57    159.403 -2   -14.834    0.001

#####
> anova(seiz.twoway, seiz.base.trt, seiz.onlybase, test="Chisq")
Analysis of Deviance Table

Model 1: y4 ~ trt * base + trt * age + age * base
Model 2: y4 ~ base * trt
Model 3: y4 ~ base
  Resid. Df Resid. Dev Df Deviance  P(>|Chi|)
1         52    136.507
2         55    149.038 -3   -12.531    0.006
3         57    159.403 -2   -10.365    0.006

```

## Comparison of Poisson Glm Models using overdispersion

```

> anova(seiz.twoway.overd,seiz.add.overd,seiz.onlybase.overd,test="Chisq")
Analysis of Deviance Table

Model 1: y4 ~ trt * base + trt * age + age * base
Model 2: y4 ~ trt + base + age
Model 3: y4 ~ base
  Resid. Df Resid. Dev Df Deviance P(>|Chi|)
1      52    136.507
2      55    144.569 -3    -8.062    0.351
3      57    159.403 -2   -14.834    0.049
#####
> anova(seiz.twoway.overd,seiz.base.trt.overd,seiz.onlybase.overd,test="Chisq")
Analysis of Deviance Table

Model 1: y4 ~ trt * base + trt * age + age * base
Model 2: y4 ~ base * trt
Model 3: y4 ~ base
  Resid. Df Resid. Dev Df Deviance P(>|Chi|)
1      52    136.507
2      55    149.038 -3   -12.531    0.165
3      57    159.403 -2   -10.365    0.122
#####
> anova(seiz.twoway.overd,seiz.add.overd,seiz.onlybase.overd,test="F")
Analysis of Deviance Table

Model 1: y4 ~ trt * base + trt * age + age * base
Model 2: y4 ~ trt + base + age
Model 3: y4 ~ base
  Resid. Df Resid. Dev Df Deviance      F >F)
1      52    136.507
2      55    144.569 -3    -8.062 1.0922 0.36069
3      57    159.403 -2   -14.834 3.0146 0.05772 .
#####
> anova(seiz.twoway.overd,seiz.base.trt.overd,seiz.onlybase.overd,test="F")
Analysis of Deviance Table

Model 1: y4 ~ trt * base + trt * age + age * base
Model 2: y4 ~ base * trt
Model 3: y4 ~ base
  Resid. Df Resid. Dev Df Deviance      F >F)
1      52    136.507
2      55    149.038 -3   -12.531 1.6977 0.1789
3      57    159.403 -2   -10.365 2.1063 0.1319
#####

```