Dealing with quasi- models in R

Ben Bolker

February 25, 2012



Computing "quasi-AIC" (QAIC), in R is a minor pain, because the R Core team (or at least the ones who wrote glm, glmmPQL, etc.) are purists and don't believe that quasi- models should report a likelihood. As far as I know, there are three R packages that compute/handle QAIC: bbmle, AICcmodavg (both on CRAN) and MuMIn (formerly known as dRedging, on r-forge).

The basic problem is that quasi- model fits with glm return an NA for the log-likelihood, while the dispersion parameter (\hat{c}, ϕ) , whatever you want to call it) is only reported for quasi- models. Various ways to get around this are:

- fit the model twice, once with a regular likelihood model (family=binomial, poisson, etc.) and once with the quasi- variant extract the log-likelihood from the former and the dispersion parameter from the latter
- only fit the regular model; extract the overdispersion parameter manually with

```
> dfun <- function(object) {
+ with(object,sum((weights * residuals^2)[weights > 0])/df.residual)
+ }
```

• use the fact that quasi- fits still contain a deviance, even if they set the log-likelihood to NA. The deviance is twice the negative log-likelihood (it's offset by some constant which I haven't figured out yet, but it should still work fine for model comparisons)

Example: use the values from one of the examples in ?glm:

```
> ## Dobson (1990) Page 93: Randomized Controlled Trial :
> counts <- c(18,17,15,20,10,20,25,13,12)
> outcome <- gl(3,1,9)
> treatment <- gl(3,3)</pre>
```

Fit Poisson and quasi-Poisson models with all combinations of predictors:

```
> glmOT.D93 <- glm(counts ~ outcome + treatment, family=poisson)
> glm0.D93 <- update(glm0T.D93, . ~ . - treatment)</pre>
> glmT.D93 <- update(glmOT.D93, . ~ . - outcome)</pre>
> glmX.D93 <- update(glmT.D93, . ~ . - treatment)
> glmQOT.D93 <- update(glmOT.D93, family=quasipoisson)</pre>
> glmQ0.D93 <- update(glm0.D93, family=quasipoisson)</pre>
> glmQT.D93 <- update(glmT.D93, family=quasipoisson)</pre>
> glmQX.D93 <- update(glmX.D93, family=quasipoisson)</pre>
  Extract log-likelihoods:
> (sum(dpois(counts,
            lambda=exp(predict(glmOT.D93)),log=TRUE))) ## by hand
[1] -23.38066
> (logLik(glmOT.D93)) ## from Poisson fit
'log Lik.' -23.38066 (df=5)
  The deviance (deviance(glmOT.D93)=5.129 is not the same as -2L (-
2*logLik(glmOT.D93)=46.761), but the calculated differences in deviance are
consistent, and are also extractable from the quasi- fit even though the log-
likelihood is NA:
> (-2*(logLik(glmT.D93)-logLik(glmOT.D93))) ## Poisson fit
'log Lik.' 5.452305 (df=3)
> (deviance(glmT.D93)-deviance(glmOT.D93)) ## Poisson fit
[1] 5.452305
> (deviance(glmQT.D93)-deviance(glmQOT.D93)) ## quasi-fit
[1] 5.452305
   Compare hand-computed dispersion (in two ways) with the dispersion com-
puted by summary.glm() on a quasi-fit:
> (dfun(glmOT.D93))
[1] 1.2933
> (sum(residuals(glmOT.D93, "pearson")^2)/glmOT.D93$df.residual)
[1] 1.2933
> (summary(glmOT.D93)$dispersion)
[1] 1
> (summary(glmQOT.D93)$dispersion)
[1] 1.2933
```

Examples

```
bbmle package (Ben Bolker), CRAN/R-forge
> library(bbmle)
> (qAIC(glmOT.D93,dispersion=dfun(glmOT.D93)))
[1] 46.15658
> (qAICc(glmOT.D93,dispersion=dfun(glmOT.D93),nobs=length(counts)))
[1] 90.15658
> ICtab(glmOT.D93,glmT.D93,glmO.D93,glmX.D93,
       dispersion=dfun(glmOT.D93),type="qAIC")
         dqAIC df
glmO.D93 0.0 3
glmX.D93 0.2
               5
glmOT.D93 4.0
glmT.D93 4.2
> ICtab(glmOT.D93,glmT.D93,glmO.D93,glmX.D93,
       dispersion=dfun(glmOT.D93),
       nobs=length(counts), type="qAICc")
         dqAICc df
glmX.D93
         0.0
          7.8
glmO.D93
               3
glmT.D93 12.0
                3
glmOT.D93 43.8
> detach("package:bbmle")
AICcmodavg package (Marc Mazerolle), CRAN
> library(AICcmodavg)
> aictab(list(glmOT.D93,glmT.D93,glmO.D93,glmX.D93),
        modnames=c("OT", "T", "O", "X"),
        c.hat=dfun(glmOT.D93))
Model selection based on QAICc :
(c-hat\ estimate = 1.2933)
  K QAICc Delta_QAICc QAICcWt Cum.Wt Quasi.LL
X 2 46.37
               0.00
                        0.98 0.98
                                     -20.19
0 4 54.16
                7.78
                         0.02 1.00
                                      -18.08
T 4 58.37
               12.00
                         0.00 1.00
                                      -20.19
OT 6 90.16
                43.78
                        0.00
                               1.00
                                      -18.08
```

> detach("package:AICcmodavg")

MuMIn package (Kamil Bartoń), r-forge

```
> library(MuMIn)
> (gg <- dredge(glmOT.D93,rank="QAIC", chat=dfun(glmOT.D93)))</pre>
Global model call: glm(formula = counts ~ outcome + treatment, family = poisson)
Model selection table
  (Int) otc trt df logLik QAIC delta weight
23.045 +
               3 -23.381 44.2 0.00 0.464
1 2.813
               1 -26.107 44.4 0.22 0.417
43.045 +
               5 -23.381 48.2 4.00 0.063
               3 -26.107 48.4 4.22 0.056
3 2.813
> (ggc <- dredge(glmOT.D93,rank="QAICc",chat=dfun(glmOT.D93)))</pre>
Global model call: glm(formula = counts ~ outcome + treatment, family = poisson)
Model selection table
  (Int) otc trt df logLik QAICc delta weight
1 2.813
               1 -26.107 46.4
                                 0.00 0.978
               3 -23.381 54.2
23.045 +
                                 7.78 0.020
               3 -26.107 58.4 12.00 0.002
               5 -23.381 90.2 43.78 0.000
43.045 +
           +
> detach("package:MuMIn")
```

Since dredge is clever, can work with quasi- models as well by using deviance():

```
> (ggqc <- dredge(glmQOT.D93,rank="QAICc",
+ chat=summary(glmQOT.D93)$dispersion))</pre>
```

gives identical results to the previous table.

Notes: ICtab only gives delta-IC, limited decimal places (on purpose, but how do you change these defaults if you want to?). Need to add 1 to parameters to account for scale parameter. When doing corrected-IC you need to get the absolute number of parameters right, not just the relative number ... Not sure which classes of models each of these will handle (lm, glm, (n)lme, lme4, mle2 ...). Remember need to use overdispersion parameter from most complex model. glmmPQL: needs to be hacked somewhat more severely (does not contain deviance element, logLik has been NA'd out).

package	lm	${\tt glm}$	(n)lme	${\tt multinom}$	polr	lme4	mle2
AICcmodavg	У	У	У	У	У	?	?
MuMIn	?	?	?	?	?	?	?
mle2	?	?	?	?	?	?	?