R package glmm

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Bacteria example 1

The MASS package contains the command glmmPQL and the bacteria data-set. The manual describes the data set as follows: "Tests of the presence of the bacteria H. influenzae in children with otitis media in the Northern Territory of Australia."

The data were fit using glmmPQL, glmm with $m = 10^3$, glmm with $m = 10^4$, glmm with $m = 10^5$. (The data did need to be reformatted, which took only a couple minutes). The parameter estimates are summarized in the following table. More model details can be seen in the output that follows the table.

	Intercept	$\operatorname{trtdrug}$	trtdrug+	I(week > 2) TRUE	ν
glmmPQL	3.41	-1.25	75	-1.61	1.99
glmm $m = 10^3$	3.02	-1.20	89	-1.44	.81
glmm $m = 10^4$	3.65	-1.36	92	-1.66	2.02
glmm $m = 10^5$	3.49	-1.65	90	-1.46	.90

It's safe to say that the bacteria glmm results with a paltry Monte Carlo sample size of $m = 10^3$ are not reliable. We conclude this because the estimates change quite a bit when $m=10^4$. The results using $m = 10^4$ are very similar to the glmmPQL results.

The glmmPQL results:

```
> bac.pql<-glmmPQL(y ~ trt + I(week > 2), random = ~ 1 | ID,
                  family = binomial, data = bacteria)
> summary(bac.pql)
Linear mixed-effects model fit by maximum likelihood
 Data: bacteria
  AIC BIC logLik
   NA
       NA
              NA
Random effects:
```

Formula: ~1 | ID

(Intercept) Residual StdDev: 1.410637 0.7800511

Variance function:

```
Structure: fixed weights
 Formula: ~invwt
Fixed effects: y ~ trt + I(week > 2)
                    Value Std.Error DF t-value p-value
(Intercept)
                 3.412014 0.5185033 169 6.580506 0.0000
trtdrug
               -1.247355 0.6440635 47 -1.936696 0.0588
               -0.754327 0.6453978 47 -1.168779 0.2484
trtdrug+
I(week > 2)TRUE -1.607257 0.3583379 169 -4.485311 0.0000
 Correlation:
                (Intr) trtdrg trtdr+
trtdrug
                -0.598
                -0.571 0.460
trtdrug+
I(week > 2)TRUE -0.537 0.047 -0.001
Standardized Within-Group Residuals:
       Min
                   Q1
                             Med
                                         QЗ
                                                   Max
-5.1985361 0.1572336 0.3513075 0.4949482 1.7448845
Number of Observations: 220
Number of Groups: 50
   The bacteria glmm results with a Monte Carlo sample size of m = 10^3:
> set.seed(1234)
> bac.glmm1<-glmm(y2~trt+I(week > 2),list(~0+ID),
family=bernoulli.glmm, data=bacteria, m=10^3, varcomps.names=c("ID"))
> summary(bac.glmm1)
glmm(fixed = y2 ~ trt + I(week > 2), random = list(~0 + ID), varcomps.names = c("ID"),
data = bacteria, family.glmm = bernoulli.glmm,
                                                  m = 10^3
Fixed Effects:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)
                3.0199
                             0.4667 6.471 9.75e-11 ***
trtdrug
                 -1.1989
                             0.4473 -2.680 0.007357 **
                            0.4742 -1.873 0.061021 .
trtdrug+
                 -0.8883
                            0.4258 -3.384 0.000716 ***
I(week > 2)TRUE -1.4407
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
```

Variance Components for Random Effects (P-values are one-tailed):

```
Estimate Std. Error z value Pr(>|z|)/2
    0.8175
                0.1635 4.998
                                 2.89e-07 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
The results from fitting the bacteria dataset with glmm and m = 10^4:
> set.seed(1234)
> bac.glmm2<-glmm(y2~trt+I(week > 2),list(~0+ID), family=bernoulli.glmm, data=bacteria, m=10^4, varcomps
> summary(bac.glmm2)
Call:
glmm(fixed = y2 ~ trt + I(week > 2), random = list(~0 + ID),
    varcomps.names = c("ID"), data = bacteria, family.glmm = bernoulli.glmm,
    m = 10^4)
Fixed Effects:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)
                 3.6514
                             0.6327 5.771 7.9e-09 ***
                             0.7461 -1.829 0.067427 .
trtdrug
                 -1.3645
trtdrug+
                 -0.9186
                             0.7619 -1.206 0.227915
I(week > 2)TRUE -1.6660
                             0.4645 -3.587 0.000334 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
Variance Components for Random Effects (P-values are one-tailed):
   Estimate Std. Error z value Pr(>|z|)/2
ID
     2.0244
               0.7515 2.694
                                  0.00353 **
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
   Results of glmm with m = 10^5:
> set.seed(1234)
> bac.glmm3<-glmm(y2~trt+I(week > 2),list(~0+ID), family=bernoulli.glmm, data=bacteria, m=10^5, varcomps
> summary(bac.glmm3)
Call:
glmm(fixed = y2 ~ trt + I(week > 2), random = list(~0 + ID),
```

varcomps.names = c("ID"), data = bacteria, family.glmm = bernoulli.glmm,

```
m = 10^5)
```

```
Fixed Effects:
```

```
Estimate Std. Error z value Pr(>|z|)
                  3.4888
                              0.4861
                                       7.178 7.08e-13 ***
(Intercept)
trtdrug
                 -1.6526
                              0.5232
                                      -3.159 0.001586 **
trtdrug+
                 -0.8968
                              0.5160
                                      -1.738 0.082196 .
I(week > 2)TRUE
                -1.4614
                              0.4334
                                      -3.372 0.000746 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
Variance Components for Random Effects (P-values are one-tailed):
   Estimate Std. Error z value Pr(>|z|)/2
     0.8999
                0.2471
                         3.641
                                  0.000136 ***
ID
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
```

2 Herd CBPP Example

The cbpp dataset is located in the lme4 package. The lme4 package describes it thusly: "Contagious bovine pleuropneumonia (CBPP) is a major disease of cattle in Africa, caused by a mycoplasma. This dataset describes the serological incidence of CBPP in zebu cattle during a follow-up survey implemented in 15 commercial herds located in the Boji district of Ethiopia. The goal of the survey was to study the within-herd spread of CBPP in newly infected herds. Blood samples were quarterly collected from all animals of these herds to determine their CBPP status. These data were used to compute the serological incidence of CBPP (new cases occurring during a given time period). Some data are missing (lost to follow-up)."

First, I fit the data using glmer in lme4. The model summary says it was fit with Adaptive Hermite Quadrature with 9 quadrature nodes. Then I fit the data using glmm with $m = 10^4$. This took 16.75 minutes on my netbook. The point estimates and some of the standard errors are very similar between the two methods of model-fitting.

	Intercept	period2	period3	period4	ν
glmer (numerical integration)	-1.40	99	-1.13	-1.58	.41
glmm $m = 10^4$	-1.42	99	-1.13	-1.58	.44

Here are the full results from glmer:

```
> summary(gm1)
```

Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [glmerMod]

Family: binomial (logit)

Formula: cbind(incidence, size - incidence) ~ period + (1 | herd)

```
Data: cbpp
```

```
AIC BIC logLik deviance df.resid
194.1 204.2 -92.0 184.1 51
```

Scaled residuals:

```
Min 1Q Median 3Q Max
-2.3816 -0.7889 -0.2026 0.5142 2.8791
```

Random effects:

Groups Name Variance Std.Dev. herd (Intercept) 0.4123 0.6421 Number of obs: 56, groups: herd, 15

Fixed effects:

Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1

Correlation of Fixed Effects:

(Intr) perid2 perid3

period2 -0.363

period3 -0.340 0.280

period4 -0.260 0.213 0.198

Next, the results using glmm with $m = 10^4$:

> summary(herd.glmm1)

Call:

```
glmm(fixed = Y ~ period, random = list(~0 + herd), varcomps.names = c("herd"),
    data = herddat, family.glmm = bernoulli.glmm, m = 10^4)
```

Fixed Effects:

Estimate Std. Error z value Pr(>|z|)

```
---
```

```
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
```

```
Variance Components for Random Effects (P-values are one-tailed):
        Estimate Std. Error z value Pr(>|z|)/2
herd 0.4354     0.2488     1.75     0.0401 *
---
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1     1
```

3 Salamander

The salamander dataset represents success or failure in matings between two types of salamanders denoted by R and W. Four types of crosses are possible: RR, RW, WR, WW. These are the fixed effects. There is a random effect for each female salamander and for each male salamander. Thus, there are two variance components: one for the females and one for the males. The response is binary: whether or not the mating was successful.

I fit the salamander data set using my glmm package (with $m = 10^4$ twice and with $m = 10^6$ once) and compared those results to the MCEM results of Booth and Hobert. They do not look so great, and the $m = 10^6$ results took 41 hours to get.

	Intercept	RW	WR	WW	$ u_F$	ν_{M}	
MCEM (B+H)	1.03	.32	-1.95	.99	1.4	1.25	
glmm $m = 10^4$	1.11	55	-3.17	21	1.21	.95	
glmm $m = 10^4$.94	76	-2.72	.0023	1.60	.99	
glmm $m = 10^{6}$	0.84	-0.81	-2.81	-0.21	1.21	1.02	

```
> set.seed(1234)
```

```
> sal.glmm3 <- glmm (Mate~Cross, random=list(~0+Female,~0+Male), varcomps.names=c("F","M"), data=salamander, family.glmm=bernoulli.glmm, m=10~4)
```

Call:

```
glmm(fixed = Mate ~ Cross, random = list(~0 + Female, ~0 + Male),
    varcomps.names = c("F", "M"), data = salamander, family.glmm = bernoulli.glmm,
    m = 10~4)
```

Fixed Effects:

```
Estimate Std. Error z value Pr(>|z|)
(Intercept)
              1.1123
                         0.2593
                                  4.290 1.79e-05 ***
CrossRW
             -0.5545
                         0.3558 -1.558
                                            0.119
CrossWR
             -3.1701
                         0.4029 -7.867 3.62e-15 ***
CrossWW
             -0.2122
                         0.3681 -0.577
                                            0.564
```

> summary(sal.glmm3)

```
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Variance Components for Random Effects (P-values are one-tailed):
  Estimate Std. Error z value Pr(>|z|)/2
   1.2087
               0.2534
                        4.769
                              9.24e-07 ***
  0.9485
               0.1809
                        5.244
                               7.86e-08 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
   Here are the results with m=10^4 but I forgot to set the seed. At least it helps us see a bit of the
variability.
> summary(sal.glmm2)
Call:
glmm(fixed = Mate ~ Cross, random = list(~0 + Female, ~0 + Male),
    varcomps.names = c("F", "M"), data = salamander, family.glmm = bernoulli.glmm,
    m = 10^4)
Fixed Effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.93879
                      0.26963 3.482 0.000498 ***
CrossRW
            -0.76157
                       0.37376 -2.038 0.041593 *
            -2.72491
                       0.40736 -6.689 2.24e-11 ***
CrossWR
CrossWW
            0.02256
                        0.37902
                                  0.060 0.952541
___
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Variance Components for Random Effects (P-values are one-tailed):
  Estimate Std. Error z value Pr(>|z|)/2
               0.2965
  1.5991
                        5.394
                              3.45e-08 ***
                        5.255 7.41e-08 ***
M 0.9908
               0.1885
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
   Here are the results with m = 10^6.
> ptm <- proc.time()
> sal.glmm3<-glmm(Mate~Cross,random=list(~0+Female,~0+Male),varcomps.names=c("F"
,"M"),data=salamander,family.glmm=bernoulli.glmm,m=10^6)
> proc.time()-ptm
```

```
system
                         elapsed
      user
148604.323
              595.454 174153.241
> summary(sal.glmm3)
Call:
glmm(fixed = Mate ~ Cross, random = list(~0 + Female, ~0 + Male),
    varcomps.names = c("F", "M"), data = salamander, family.glmm = bernoulli.glm
m,
    m = 10^6)
Fixed Effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)
              0.8413
                         0.2756
                                  3.052 0.00227 **
CrossRW
             -0.8074
                         0.3737 -2.161 0.03072 *
CrossWR
             -2.8062
                         0.4097 -6.849 7.43e-12 ***
CrossWW
             -0.2135
                         0.3887 -0.549 0.58289
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
Variance Components for Random Effects (P-values are one-tailed):
  Estimate Std. Error z value Pr(>|z|)/2
    1.2090
               0.2443
                        4.948
                                3.74e-07 ***
    1.0196
               0.2013
                        5.065
                                2.04e-07 ***
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1
> sal.glmm3$beta.pql
[1] 0.83806013 -0.57917030 -2.44205490 -0.01778234
> sal.glmm3$nu.pql
[1] 1.122464 1.036371
```

4 Murder

Subjects were asked how many victims of homicide they personally knew. The data set is from Agresti's Categorical Data Analysis book. I found similar answers from my glmm package as from glmmPQL.

The results from my package:

```
set.seed(1234)
murder.glmm<- glmm(y~race ,random=list(~0+black,~0+white), varcomps.names=c("black","white"), data=murde
> summary(murder.glmm)
```

```
Call:
glmm(fixed = y ~ race, random = list(~0 + black, ~0 + white),
    varcomps.names = c("black", "white"), data = murder, family.glmm = poisson.glmm,
    m = 10^4)
Fixed Effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.42003
                        0.06428 6.534 6.40e-11 ***
                        0.07021 -4.726 2.29e-06 ***
raceWhite
           -0.33179
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Variance Components for Random Effects (P-values are one-tailed):
       Estimate Std. Error z value Pr(>|z|)/2
black 6.468e-10 3.452e-09
                             0.187
                                        0.426
white 2.667e-10 1.596e-09
                           0.167
                                        0.434
   When I make the sample size drastically smaller so that the analysis takes only about a minute, the
results are very similar still.
> summary(murder.glmm)
Call:
glmm(fixed = y ~ race, random = list(~0 + black, ~0 + white),
    varcomps.names = c("black", "white"), data = murder, family.glmm = poisson.glmm,
    m = 10^2
Fixed Effects:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.42003
                        0.06428
                                  6.534 6.39e-11 ***
                        0.07021 -4.726 2.29e-06 ***
raceWhite
            -0.33179
Signif. codes: 0 *** 0.001 ** 0.01 * 0.05 . 0.1 1
Variance Components for Random Effects (P-values are one-tailed):
       Estimate Std. Error z value Pr(>|z|)/2
black 1.190e-09 1.718e-09
                           0.693
                                        0.244
white 1.070e-08 1.440e-08 0.743
                                        0.229
```

The murder model resulting from glmmPQL:

> murder.pql<-glmmPQL(y~race,random=~1|race,data=murder,family=poisson)iteration 1

```
> summary(murder.pql)
Linear mixed-effects model fit by maximum likelihood
 Data: murder
  AIC BIC logLik
   NA NA
Random effects:
 Formula: ~1 | race
         (Intercept) Residual
StdDev: 9.157794e-06 0.4647694
Variance function:
 Structure: fixed weights
 Formula: ~invwt
Fixed effects: y ~ race
                 Value Std.Error
                                    DF
                                         t-value p-value
(Intercept) 0.4200335 0.02989812 1306 14.04883
            -0.3317900 0.03265396
raceWhite
                                     0 -10.16079
                                                     NaN
 Correlation:
          (Intr)
raceWhite -0.916
Standardized Within-Group Residuals:
       Min
                   Q1
                             Med
                                         QЗ
                                                   Max
-0.9104427 -0.1899269 -0.1899269 -0.1899269 12.1624898
Number of Observations: 1308
Number of Groups: 2
Warning message:
In pt(-abs(tTable[, "t-value"]), tTable[, "DF"]) : NaNs produced
```

5 Reformatting the Datsets

5.1 Bacteria Reformatting

The issue with the bacteria dataset is the response was y/n rather than 1/0. I created a new response that changed the y to 1 and the n to 0.

bacteria\$y2<-as.integer(bacteria\$y)-1</pre>

5.2 CBPP Reformatting

The cbpp dataset was created for binomial but my package was written for Bernoulli responses. In other words, my package needs a row for each success or failure. I did this in the following way:

```
cbpp$nonincidence<-cbpp$size-cbpp$incidence #number of "failures"
herddat<-matrix(data=NA,nrow=842,ncol=3)
colnames(herddat)<-c("Y","period","herd")</pre>
rowid<-1
for(i in 1:nrow(cbpp)){
#make a row for each one of the incidences
ntimes<-cbpp[i,2]</pre>
if(ntimes>0){
for(j in 1:ntimes){
herddat[rowid,]<-c(1,cbpp[i,4],cbpp[i,1])
rowid<-rowid+1
}
#make a row for each of the nonincidences
ntimes<-cbpp[i,5]</pre>
if(ntimes>0){
for(j in 1:ntimes){
herddat[rowid,]<-c(0,cbpp[i,4],cbpp[i,1])
rowid<-rowid+1
}
}
}
herddat<-as.data.frame(herddat)
herddat$herd<-as.factor(herddat$herd)
herddat$period<-as.factor(herddat$period)
```