ADVANCED BAYESIAN MODELING

Ebola Data Example: Overdispersed Model

Ebola Outbreaks Data

```
y_i = deaths in outbreak i, out of n_i human cases
```

$$x_{i1}, x_{i2}, x_{i3} = \text{indicators of ebolavirus type (BDBV, EBOV, SUDV)}$$

$$x_{i4}$$
 = year outbreak began (centered and scaled)

$$i=1,\ldots,17$$

Model Allowing Overdispersion

$$y_i \mid \beta, X_i \sim \text{indep. Bin}(n_i, p_i)$$

$$\operatorname{logit}(p_i) = X_i \beta + \epsilon_i \qquad \epsilon_i \sim \operatorname{iid} \operatorname{N}(0, \sigma_{\epsilon}^2)$$

Random effects ϵ_i allow for overdispersion.

We will use the same scaled- t_1 priors on coefficients in β as before, and a flat hyperprior on σ_{ϵ} (approximated by a uniform).

3

```
In ebola2.bug:
model {
  for (i in 1:length(deaths)) {
    deaths[i] ~ dbin(prob[i], cases[i])
    logit(prob[i]) <- betavirus[virus[i]] + betavear*vearscaled[i] + epsilon[i]</pre>
    epsilon[i] ~ dnorm(0,1/sigmaepsilon^2)
    deathsrep[i] ~ dbin(prob[i], cases[i])
  for (j in 1:max(virus)) {
    betavirus[j] ~ dt(0, 0.01, 1)
  betayear ~ dt(0, 0.16, 1)
  sigmaepsilon ~ dunif(0,10)
```

Data is set up as before, but initializations of the 4 chains now include sigmaepsilon:

```
Resolving undeclared variables
  Allocating nodes
Graph information:
  Observed stochastic nodes: 17
  Unobserved stochastic nodes: 39
  Total graph size: 221
Initializing model
 > update(m2, 1000) # burn-in
 > x2 <- coda.samples(m2, c("betavirus", "betayear", "sigmaepsilon"), n.iter=2000)
 | *************** 100%
```

> m2 <- jags.model("ebola2.bug", d2, inits2, n.chains=4, n.adapt=1000)</pre>

Compiling model graph

> gelman.diag(x2, autoburnin=FALSE)
Potential scale reduction factors:

	Point	est.	Upper	C.I.
betavirus[1]		1.05		1.11
betavirus[2]		1.02		1.04
betavirus[3]		1.01		1.02
betayear		1.05		1.14
sigmaepsilon		1.01		1.01

Multivariate psrf

1.05

Close to convergence, but continue burn-in just to be sure ...

> gelman.diag(x2, autoburnin=FALSE)
Potential scale reduction factors:

	Point	est.	Upper	C.I.
betavirus[1]		1.01		1.02
betavirus[2]		1.00		1.01
betavirus[3]		1.01		1.02
betayear		1.01		1.01
sigmaepsilon		1.02		1.04

Multivariate psrf

1.01

Need more iterations for inference ...

Effective sample sizes now adequate.

```
> summary(x2[,c("betavirus[1]","betavirus[2]","betavirus[3]",
+
               "betayear", "sigmaepsilon")])
. . .
                       SD Naive SE Time-series SE
               Mean
betavirus[1] -0.5122 0.5712 0.0028558
                                          0.019973
betavirus[2] 1.1237 0.2479 0.0012397
                                         0.007913
betavirus[3] 0.2233 0.3688 0.0018440
                                         0.016826
betayear -0.2605 0.4306 0.0021532 0.017559
sigmaepsilon 0.7040 0.1877 0.0009386
                                          0.003780
. . .
```

2.5% 25% 50% 75% 97.5% betavirus[1] -1.6614 -0.87322 -0.5112 -0.14831 0.6242 betavirus[2] 0.6216 0.96729 1.1228 1.28084 1.6215 betavirus[3] -0.5238 -0.00676 0.2187 0.45343 0.9637 betayear -1.0883 -0.53952 -0.2549 0.02211 0.5749 sigmaepsilon 0.4193 0.57087 0.6769 0.80514 1.1432

Note:

- ▶ betayear could plausibly be 0 (no time effect).
- ▶ sigmaepsilon is apparently not unduly restricted by its prior upper bound of 10.

Set up for chi-square discrepancy check, as before:

```
> probs <- as.matrix(x2)[, paste("prob[",1:nrow(ebola),"]", sep="")]</pre>
> deathsrep <- as.matrix(x2)[, paste("deathsrep[",1:nrow(ebola),"]", sep="")]</pre>
> Tchi <- numeric(nrow(deathsrep))</pre>
> Tchirep <- numeric(nrow(deathsrep))</pre>
> for(s in 1:nrow(deathsrep)){
    Tchi[s] <- sum((ebola$Deaths - ebola$Cases*probs[s,])^2 /</pre>
                     (ebola$Cases*probs[s,]*(1-probs[s,])))
+
    Tchirep[s] <- sum((deathsrep[s,] - ebola$Cases*probs[s,])^2 /</pre>
                        (ebola$Cases*probs[s,]*(1-probs[s,])))
+ }
```

```
> mean(Tchirep >= Tchi)
[1] 0.46925
```

No overdispersion problems this time.

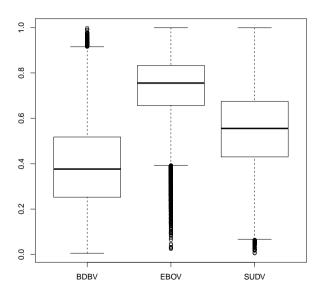
Could also check ϵ_i s for

- ► Non-normality
- ▶ Relationship to country most affected

These were checked (results not shown), and no problems found.

Investigate fatality rates of viruses for a "new" outbreak at average year (mean(ebola\$Year)):

```
> ilogit <- function(x) 1/(1+exp(-x))</pre>
> betavirus <- as.matrix(x2)[, paste("betavirus[",1:3,"]", sep="")]</pre>
> sigmaepsilon <- as.matrix(x2)[, "sigmaepsilon"]</pre>
> newepsilon <- rnorm(length(sigmaepsilon), 0, sigmaepsilon)</pre>
> pBDBV.post <- ilogit(betavirus[.1] + newepsilon)</pre>
> pEBOV.post <- ilogit(betavirus[.2] + newepsilon)</pre>
> pSUDV.post <- ilogit(betavirus[,3] + newepsilon)</pre>
> boxplot(list(BDBV=pBDBV.post,EBOV=pEBOV.post,SUDV=pSUDV.post))
```



For example, the probability someone is more likely to die in a new EBOV outbreak than in a new SUDV outbreak:

```
> mean(pEBOV.post > pSUDV.post)
[1] 0.97415
```

The 2014 EBOV outbreak in DRC had 66 human cases and 49 deaths.

How many deaths does our model predict?