

Lin models and BUGS

Normal model for data $y_i, i=1, \dots, n$:

- $y_i \sim N(\mu_i, \tau)$ with $\tau=1/\sigma^2$
and $\mu_i = \alpha_0 + \alpha_1 X_{i1} + \dots + \alpha_p X_{ip}$
- α_0 is **intercept** (mean of y when all X are at zero values).
- α_j is **slope** for covariate X_j . When X_j is increased by one unit, the mean μ_i is increased by α_j .
- Could predict y_i for some hypothetical X_i^*

Lin models and BUGS

- Conditional joint probability density of all data is:

$$\pi(y|\alpha, \tau) = \prod_{i=1}^n \mathbf{N}(y_i|\mu_i, \tau)$$

(conditional independence, given μ_i, τ)

- This is also "likelihood function" of α, τ :
 $L(\alpha, \tau ; y)$ for given data y .

Lin models and BUGS

- Posterior density of parameters:

$$\pi(\alpha, \tau | y) \propto \prod_{i=1}^n \text{N}(y_i | \mu_i, \tau) \times \pi(\alpha, \tau)$$

- in BUGS:

```
for(i in 1:n){  
  y[i] ~ dnorm(mu[i],tau); mu[i] <- inprod(a[],X[i,]) }  
tau ~ dgamma(0.001,0.001)  
for(j in 1:p){ a[j] ~ dnorm(0,0.001) }
```

Lin models and BUGS

- Easy to experiment with different priors in BUGS, also multivariate priors (e.g. Zellner's)
 - how sensitive are the results?
- May be useful to standardize covariates, to reduce posterior correlation between parameters, and possibly for better MCMC convergence.

ANOVA and BUGS

- Covariates **X are categorical variables.**
- Measurement y is obtained from some individuals (experiments) within some category, defined by X .
- Using the intercept term, the mean in category X_j would be $\alpha_0 + \alpha_j$ for all measurements there.
 - parameters α_0 and α_j not identifiable from data as such.
 - Need constraints: CR or STZ,
or use "simple model" without α_0 .

ANOVA and BUGS

- Only one categorical covariate: "one way anova"
- Two categorical covariates: "two way anova"
 - only main effects included, or
 - interactions included (then all the corresponding main effects need to be included)
- Compare the main effect parameters to see if different levels of categorical covariates have an effect on response. (e.g. box plots in BUGS).
 - e.g. means at different age groups → is there a pattern? (linearity over groups is not assumed).

ANOVA and BUGS

- Estimate interactions to see if some combination of categorical covariate levels in A and B have a combined effect that could not be explained by their main effects only.
 - i.e. the mean response in category $A_k B_r$ may not be simply described by $\alpha_k + \beta_r$ but as $\alpha_k + \beta_r + \gamma_{k,r}$.
 - interaction terms would again lead to unidentifiability \rightarrow need CR or STZ for them too.
 - Multifactor analysis, higher order interactions, but try to keep it as simple as possible.

ANOVA and BUGS

- Typical covariates:
 - Age groups
 - Gender
 - 'Treatment' groups
 - drug/placebo
 - smoking/non-smoking
 - dose groups: low dose, medium dose, high dose.
 - Other classification, e.g. econ status, residence.
- Aim to estimate (main) effects of these, and possible interaction effects.

ANOVA and BUGS

- **BUGS:**

- **individual data format:**

- ```
for(i in 1:n){ y[i] ~ dnorm(mu[i],tau) }
```

- where we loop over n individual measurements.

- **tabular data format:**

- ```
for(k in 1:K){
```

- ```
 for(r in 1:R){ y[k,r] ~ dnorm(mu[k,r],tau) }
```

- where we loop over R measurements in K categories.

- define mu[i] or mu[k,r] accordingly !

# ANOVA and BUGS

- BUGS, individual data format:
  - Could write out the linear predictor as
$$\mu[i] \leftarrow a_0 + a_1 * \text{equals}(X[i], 1) + \dots + a_p * \text{equals}(X[i], p)$$
for different levels of categorical variable X.
  - Need CR or STZ for  $a_0, \dots, a_p$ , **or** eliminate  $a_0$ .
  - Could use **dummy variables**, which are defined according to CR or STZ, so that the constraints become imposed via these dummies.
  - Compact expression:  $\text{inprod}(a[], X[i,])$
  - Similar idea for tabular data format.

# ANCOVA and BUGS

- In the same model, in linear predictor, we include:
  - Continuous covariates  $X$ , as before with normal linear models.
  - Categorical covariates  $X$ , as before with anova models
  - Could model e.g. different regression lines in each categorical group.
    - special case: common slope across groups
    - special case: common intercept across groups
    - etc
  - BUGS implementation is analogous to previous.

# GLM and BUGS

- Extending the concept of linear models.
- E.g. Binomial data  $y_i \sim \text{Bin}(p_i, n_i)$ , where we want to explain  $p$  by some covariates  $X$ . Link function needed:

$$\text{logit}(p_i) = \alpha_0 + \alpha_1 X_{i1} + \dots + \alpha_p X_{ip}$$

When all  $X=0$ , we get  $p_0 = \exp(\alpha_0)/(1+\exp(\alpha_0))$

and if also  $\alpha_0 = 0$ , then  $p_0 = 0.5$ .

$p_0$  could represent the reference category, if  $X$  are categorical, or the success probability for an individual with all  $X=0$ , if  $X$  is continuous.

# GLM and BUGS

- Typically, noninformative priors as default.
- BUGS:

```
for(i in 1:n){
 y[i] ~ dbin(p[i],n[i]); logit(p[i]) <- inprod(a[],X[i,]) }
 for(j in 1:p){ a[j] ~ dnorm(0,0.001) }
```
- Make use of available link functions as above, or solve  $p[i] = f(\text{inprod}(a[],X[i,]))$  and write it as expression.

# GLM and BUGS

- Different link functions in different GLMs, e.g. log-linear link in Poisson models.
- Interpretation of GLM parameters depends on the link.

– e.g. with log-linear Poisson model:

$$\text{Log}(\lambda_i) = \alpha_0 + \alpha_1 X_{i1} + \dots + \alpha_p X_{ip}$$

the effect of increasing covariate  $X_j$  by one unit is multiplicative for  $\lambda_i$ :  $\exp(\alpha_j) \rightarrow$  this could be monitored in BUGS for reporting the results. A positive effect  $\alpha_j > 0$  corresponds to  $\exp(\alpha_j) > 1$ .

# LM, ANOVA, ANCOVA, GLM and BUGS

- In all the above, practical interest could be
  - about **estimates** of model parameters in the linear predictor. These describe effects of covariates of interest. In  $N(\mu_i, \sigma^2)$ -models we also get estimates of  $\sigma$ , which may not be of primary interest (but uncertainty about it will be counted in the joint posterior distribution). Might study  $1 - \sigma^2/s^2$  to see the proportional reduction of uncertainty we achieve by incorporating the  $X$  in our model.
  - about **predictions** of  $y$ , under different  $X$ .

# LM, ANOVA, ANCOVA, GLM and BUGS

- DIC readily available for model comparison, but not always applicable! (See warnings in manual).
- Missing data in  $y$  will be predicted. (No effect on parameter estimates).
- Missing data in  $x$  will require a specification of  $\pi(x \mid \text{parameters})$ . If the corresponding  $y$  is known, this will influence parameter estimates, because it will describe what are probable values for the missing  $x$ . Technically: just add the conditional model for  $x$  in BUGS code.



# LM, ANOVA, ANCOVA, GLM and BUGS

- Censored data  $y$ :
  - left censoring
  - right censoring
  - interval censoring
  - implement using  $I(\cdot)$ -function which will add the correct "likelihood contribution"  $P(y_i > a)$ ,  $P(y_i < b)$ , or  $P(a < y_i < b)$  from each such observation.
  - truncated distribution is a different problem. Will be better addressed in OpenBUGS ( $T(\cdot)$ -function).
- Distributions not directly available in BUGS:
  - Try zeros trick or ones trick.