

## Class 4: Hierarchical generalised linear models

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## Learning outcomes:

- ▶ Understand the modelling implications of moving from linear to hierarchical generalised linear models (HGLMs)
- ▶ Know some of the different versions of Hierarchical GLMs
- ▶ Be able to fit HGLMS in JAGS
- ▶ Be able to expand and summarise fitted models

# From LMs to HGLMs

- ▶ Reminder: a hierarchical model has prior distributions on the parameters which depend on further parameters
- ▶ A generalised linear model is one in which the probability distribution is not normal, and a link function serves to match the mean of the distribution to the covariates
- ▶ Within this framework, we can borrow the ideas from the previous class to create hierarchical GLMs
- ▶ We will go through four examples: binomial-logit, Poisson, robust regression, and ordinal regression

## Example 1: binomial-logit

- ▶ In class 2, we met the Binomial-logit model for binary data:

$$y_i \sim \text{Bin}(1, p_i), \text{logit}(p_i) = \alpha + \beta x_i$$

Here  $\text{logit}(p_i)$  is the link function, and equal to  $\log\left(\frac{p_i}{1-p_i}\right)$  and transforms the bounded probabilities into an unbounded space

- ▶ If we have non-binary data we just change the likelihood:

$$y_i \sim \text{Bin}(N_i, p_i), \text{logit}(p_i) = \alpha + \beta x_i$$

- ▶ In a hierarchical version of this model, we vary the *latent parameters*  $\alpha$  and  $\beta$  and give them prior distributions

# The swiss willow tit data

```
swt = read.csv('../data/swt.csv')  
head(swt)
```

##	rep.1	rep.2	rep.3	c.2	c.3	elev	forest	dur.1	day.2	day.3	length	alt
## 1	0	0	0	0	0	420	3	240	58	73	6.2	Low
## 2	0	0	0	0	0	450	21	160	39	62	5.1	Low
## 3	0	0	0	0	0	1050	32	120	47	74	4.3	Med
## 4	0	0	0	0	0	1110	35	180	44	71	5.4	Med
## 5	0	0	0	0	0	510	2	210	56	73	3.6	Low
## 6	0	0	0	0	0	630	60	150	56	73	6.1	Low

## A hierarchical model

- Suppose we want to fit a model on the sum  $y_i = \text{rep.1} + \text{rep.2} + \text{rep.3}$ :

$$y_i \sim \text{Bin}(N_i, p_i), \text{logit}(p_i) = \alpha_{\text{altitude}_i} + \beta_{\text{altitude}_i} x_i$$

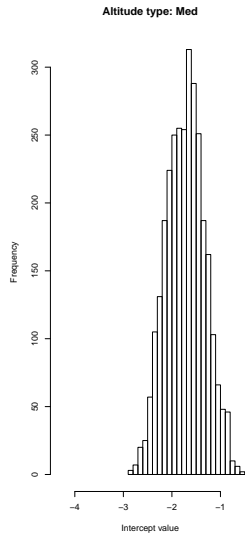
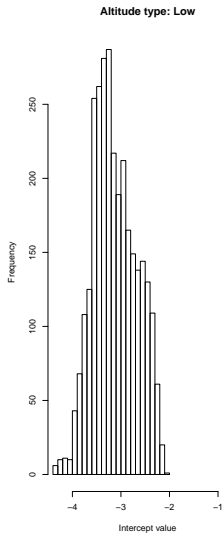
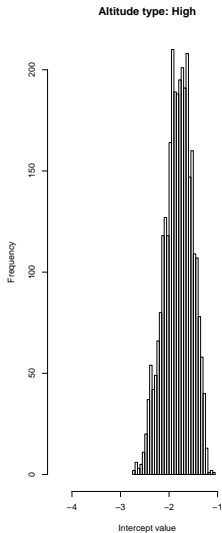
where  $x_i$  is the percentage of forest cover

- ▶ What prior distributions should we use for  $\alpha$  and  $\beta$ ?
- ▶ Useful side note: A value of 10 on the logit scale leads to a probability of about 1, and a value of -10 leads to a probability of about 0 (you can test this by typing `inv.logit(10)`) so I wouldn't expect the value of  $\text{logit}(p_i)$  to ever get much bigger than 10 or smaller than -10
- ▶ I have no idea whether we are more likely to find these birds in high percentage forest or low, so I'm happy to think that  $\beta$  might be around zero, and be positive or negative. Forest cover ranges from 0 to 100 so that suggests that  $\beta$  is every likely to be bigger than 0.1 or smaller than -0.1. Perhaps  $\beta \sim N(0, 0.1^2)$  is a good prior
- ▶ It looks to me like the intercept is very unlikely to be outside the range (-10, 10) so perhaps  $\alpha \sim N(0, 5^2)$  is appropriate

# JAGS code

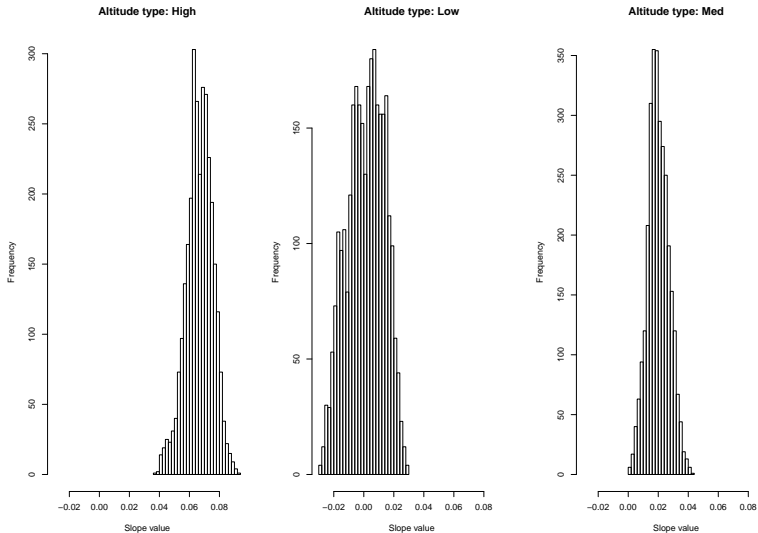
```
jags_code = '
model{
  # Likelihood
  for(i in 1:N) {
    y[i] ~ dbin(p[i], N_exp[i])
    logit(p[i]) <- alpha[alt[i]] + beta[alt[i]]*x[i]
  }
  # Priors
  for(j in 1:N_alt) {
    alpha[j] ~ dnorm(mu_alpha, sigma_alpha^-2)
    beta[j] ~ dnorm(mu_beta, sigma_beta^-2)
  }
  mu_alpha ~ dnorm(0, 5^-2)
  mu_beta ~ dnorm(0, 0.1^-2)
  sigma_alpha ~ dt(0,5,1)T(0,)
  sigma_beta ~ dt(0,5,1)T(0,)
}
'
```

# Model fit - intercepts

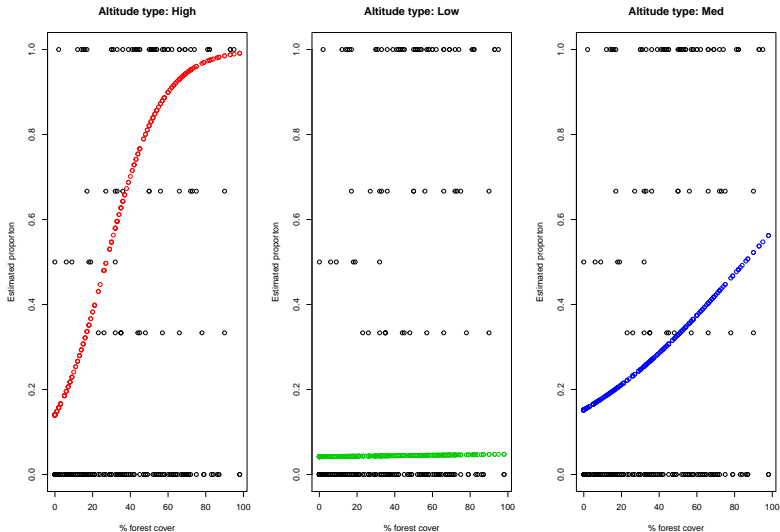




# Model fit - Slopes



# Model fit - estimated mean proportions



## Type 2: Poisson HGLMs

- ▶ For a Poisson distribution there is no upper bound on the number of counts
- ▶ We just change the likelihood (to Poisson) and the link function (to log):

$$y_i \sim Po(\lambda_i), \log(\lambda_i) = \alpha + \beta x_i$$

- ▶ We can now add our hierarchical layers into  $\alpha$  and  $\beta$ , or...
- ▶ Another way we can add an extra layer is by giving  $\log(\lambda_i)$  a probability distribution rather than setting it to a value
- ▶ This is a way of introducing *over-dispersion*, i.e. saying that the data are more variable than that expected by a standard Poisson distribution with our existing covariates

# An over-dispersed model

- ▶ The over-dispersed model looks like:

$$y_i \sim Po(\lambda_i), \log(\lambda_i) \sim N(\alpha + \beta x_i, \sigma^2)$$

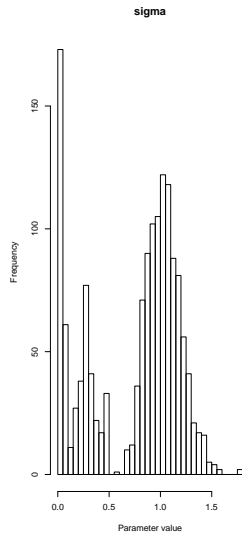
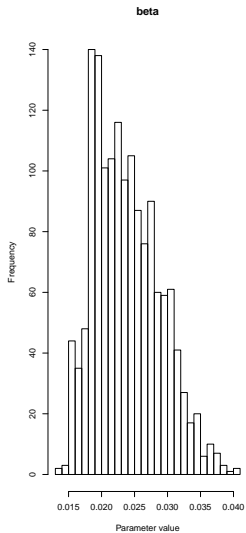
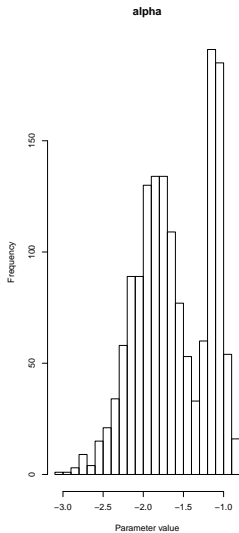
where  $\sigma$  is the over-dispersion parameter

- ▶ We now need to estimate prior distributions for  $\alpha$ ,  $\beta$ , and  $\sigma$
- ▶ We will use the SWT data again, but pretend that we didn't know that they had gone out  $N$  times looking for the birds

## JAGS code for OD Poisson

```
jags_code = '  
model{  
  # Likelihood  
  for(i in 1:N) {  
    y[i] ~ dpois(exp(log_lambda[i]))  
    log_lambda[i] ~ dnorm(alpha + beta * x[i], sigma^-2)  
  }  
  alpha ~ dnorm(0, 5^-2)  
  beta ~ dnorm(0, 0.1^-2)  
  sigma ~ dt(0,5,1)T(0,)  
}
```

# Model run



# Notes about OD Poisson model

- ▶ The way to think about OD models is via the data generating process. Draw a DAG and think about how these processes might arise
- ▶ We could compare this model to one without over dispersion via DIC (or if time, cross validation). We should also compute a posterior predictive distribution for full comparison
- ▶ In general, the parameter values (i.e. alpha and beta) tend to be more uncertain when you add in over dispersion
- ▶ Also in the data set is a variable called dur which represents how long they spent looking for the birds. This could be added in as an offset via the likelihood:

```
y[i] ~ dpois(dur[i] * exp(log_lambda[i]))
```

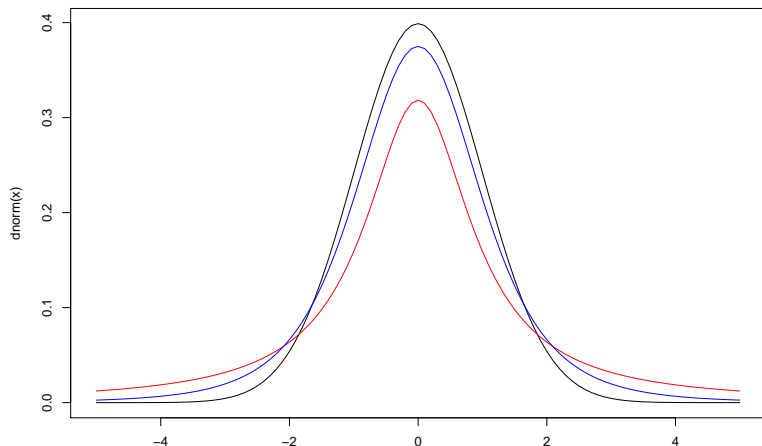
## Type 3: $t$ -distributed HGLMs

- ▶ How do Bayesians deal with outliers?
- ▶ A common view is that we should delete these observations before we run the model, but what if we can't find a reason for doing so
- ▶ A good Bayesian will include outliers as part of the model.
- ▶ One way of doing this is by switching from a normal distribution to a  $t$ -distribution



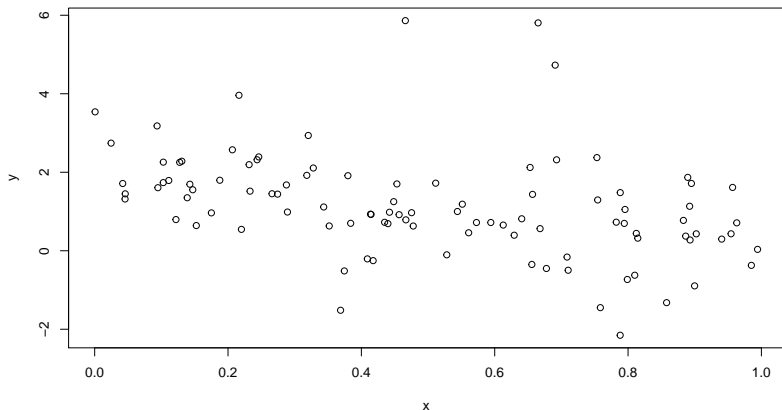
## Normal vs $t$

```
curve(dnorm, from = -5, to = 5)  
curve(dt(x, df = 1), add = TRUE, col = 'red')  
curve(dt(x, df = 4), add = TRUE, col = 'blue')
```



## Polluted data

- Suppose we had some data which looked like this:



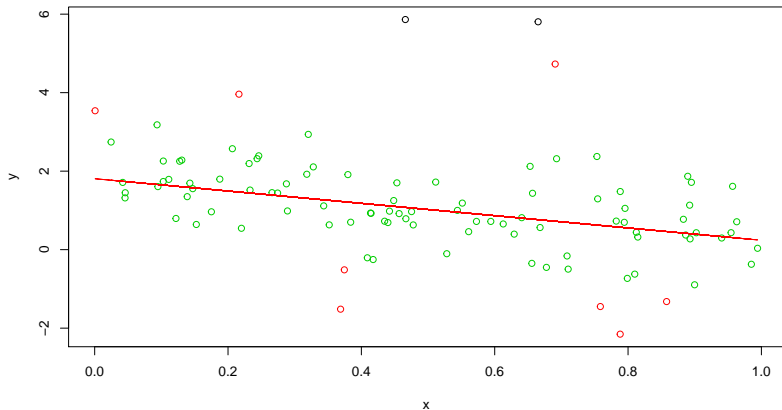
There are a few observations here which look a bit odd

## JAGS code for a $t$ -model

```
jags_code = '  
model{  
  # Likelihood  
  for(i in 1:N) {  
    y[i] ~ dt(alpha + beta * x[i], sigma, df[i] + 1)  
    df[i] ~ dbin(p, 10)  
  }  
  p ~ dunif(0, 1)  
  alpha ~ dnorm(0, 1^-2)  
  beta ~ dnorm(0, 1^-2)  
  sigma ~ dt(0,1,1)T(0,)  
}  
,
```

## Output from the model

```
dfs = jags_run$BUGSoutput$median$df
pars = jags_run$BUGSoutput$mean
plot(x, y, col = as.factor(dfs))
lines(x, pars$alpha + pars$beta*x, col = 'red')
```



## Prior distributions on the degrees of freedom

- ▶ Here I've set a prior distribution on the degrees of freedom parameter to be Binomial with the maximum value to be  $10+1 = 11$
- ▶ The probability of each observation being an outlier is  $p$ , set to be uniform between 0 and 1
- ▶ We thus also create a posterior distribution for the probability that each observation is an outlier
- ▶ The Binomial distribution we use has a peak at the degrees of freedom being 6 or 7, we might instead use a discrete uniform prior though this is harder to code in JAGS/Stan

## Type 4: Ordinal data HGLMs

- ▶ Often we have a response variable which is ordinal, e.g. disagree, neutral, agree, etc
- ▶ There are lots of different (and complicated) ways to model such data
- ▶ Perhaps the easiest is to think of it as a hierarchical model with 'cut-points' on a latent linear regression

## An ordinal model example

- Suppose  $y_i = \{\text{disagree, neutral, agree}\}$  and we make it dependent on a latent continuous variable  $z_i$ , so that :

$$y_i = \begin{cases} \text{agree} & \text{if } z_i > 0.5 \\ \text{neutral} & \text{if } -0.5 < z_i \leq 0.5 \\ \text{disagree} & \text{if } z_i \leq -0.5 \end{cases}$$

- We then give  $z_i$  a prior distribution, e.g.  $N(\beta_0 + \beta_1 x_i, \sigma^2)$

## Fitting ordinal models in JAGS

```
jags_code = '  
model{  
  # Likelihood  
  for(i in 1:N) {  
    z[i] ~ dnorm(alpha + beta * x[i], sigma^-2)  
    y[i] ~ dinterval(z[i], cuts)  
  }  
  alpha ~ dnorm(0, 100^-2)  
  beta ~ dnorm(0, 100^-2)  
  sigma ~ dt(0, 10, 1)T(0, )  
}  
,
```

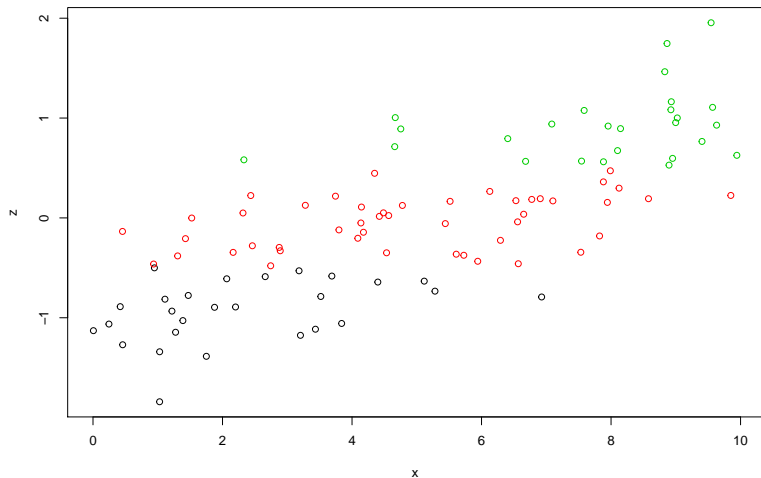


## Simulating some example data

```
N = 100
alpha = -1
beta = 0.2
sigma = 0.51
set.seed(123)
x = runif(N, 0, 10)
cuts = c(-0.5, 0.5)
z = rnorm(N, alpha + beta * x, sigma)
y = findInterval(z, cuts)
```

## Simulated data - plot

```
plot(x, z, col = y + 1)
```



## Fitting in JAGS - needs initial values

```
jags_inits = function() {  
  z = runif(N, -0.5, 0.5)  
  z[y==0] = runif(sum(y==0), -1, -0.5)  
  z[y==2] = runif(sum(y==2), 0.5, 1)  
  return(list(z = z))  
}  
  
jags_run = jags(data = list(N = N,  
                             y = y,  
                             x = x,  
                             cuts = cuts),  
               inits = jags_inits,  
               parameters.to.save = c('alpha',  
                                       'beta',  
                                       'sigma'),  
               model.file = textConnection(jags_code))
```

# Output

```
print(jags_run)
```

```
## Inference for Bugs model at "5", fit using jags,  
## 3 chains, each with 2000 iterations (first 1000 discarded)  
## n.sims = 3000 iterations saved  
##           mu.vect sd.vect  2.5%   25%   50%   75%  97.5%  
## alpha      -1.024   0.148 -1.340 -1.119 -1.014 -0.924 -0.764 1  
## beta        0.203   0.027  0.155  0.185  0.202  0.220  0.261 1  
## sigma       0.524   0.073  0.400  0.469  0.518  0.570  0.689 1  
## deviance    0.000   0.000  0.000  0.000  0.000  0.000  0.000 1  
##  
## For each parameter, n.eff is a crude measure of effective sam  
## and Rhat is the potential scale reduction factor (at converge  
##  
## DIC info (using the rule, pD = var(deviance)/2)  
## pD = 0.0 and DIC = 0.0  
## DIC is an estimate of expected predictive error (lower devian
```

# Summary

- ▶ We have now seen a number of different types of hierarchical GLM
- ▶ Many of the ideas of hierarchical linear models transfer over, but we can explore richer behaviour with hierarchical GLMs
- ▶ These have all used the normal, binomial or Poisson distribution at the top level, and have allowed for over-dispersion, robustness, and ordinal data, to name just three