

Lab 9 + GLS and Mixed effect MOdels

Bob Douma

3 December 2018

Learning goals

You will learn how to:

1. Estimate the parameters of a model that contains both a continuous and a categorical predictor through maximum likelihood
2. Estimate the parameters of a model with the variance varying as a function of a covariate (**gls**)
3. Apply mixed effect models to data with nested structures

Fitting models containing categorical predictors

1. Take the fifth dataset of the six datasets you have worked with earlier on. Assume that the function was generated by a decreasing exponential function ae^{-bx} and estimate the parameters a and b .

```
read.csv("shapes.csv") # and select fifth dataset
# test dataset five for differences between groups
nll0 = function(par,dat){
  a = par[1]
  b = par[2]
  ymean = a*exp(-b*dat$x)
  nll = -sum(dpois(dat$y,lambda=ymean),log=T)
  return(nll)
}

par=c(4,0.2)
opt1 = optim(par=par,fn=nll,dat=dat)
```

2. Adjust the likelihood function such that it can accomodate for different values of b depending on the group an observation belong to. The dataset consist of a column **group** with two levels that indicate to which group an observation belongs. Use the following pseudocode to achieve this and/or check page 305 for in inspiration:
 - a. Adapt the likelihood function such that the parameter **b** depends on the group.
 - b. Adjust the starting values so it contains multiple starting values for **b**
3. Estimate the parameters a and b when letting b depend on the group. Compare the negative loglikelihood of this model with the model fitted in question 1. Which has a better fit?
4. Apply model selection techniques (Likelihood ratio test, AIC or BIC) to select the most parsimonious model. Are the models nested? Which model is preferred?

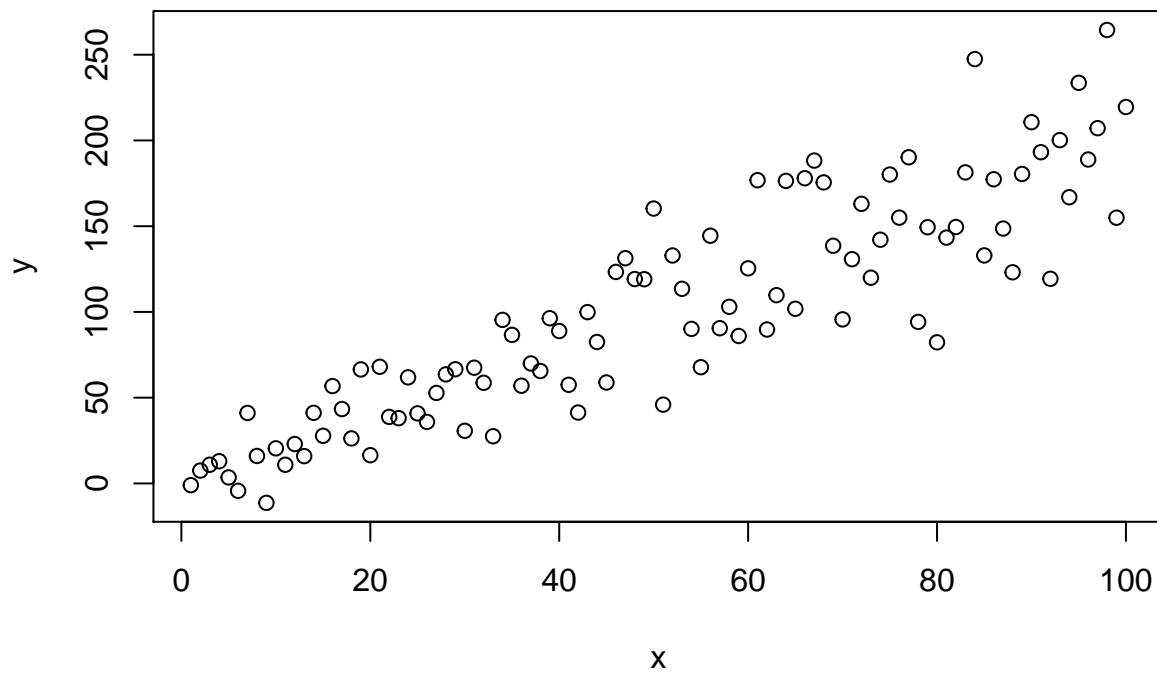
Fitting models with the heterogenous variance

It is common to observe in your data that the variance of your data is not constant along x . In the above example we observed a decreasing variance with increasing x . In case of the Poisson distribution, the relationship between the mean and the variance is fixed through λ . For other probability distributions with ≥ 2 parameters the variance can be modelled (somewhat) independent of each other. A classic example is the normal distribution with μ equal to the mean of the distribution and σ to the square root of the variance.

Traditionally, when the variance increases with x log transformations are applied. However, the variance can also be modelled explicitly. The purpose of this exercise is to show you give you insight how this can be done (by showing a simple but wrong approach), followed by the correct, but canned approach `gls` in R.

To illustrate the principle, we generate data from scratch first with constant variance, then we heterogeneous variance:

```
x = seq(1,100,length.out = 100)
y = 2 + 2 * x + rnorm(100,0,20)
plot(y~x)
```



1. Estimate the parameters of the model through applying the Bolker approach. Make two models, one with constant variance and another one with the variance as a function of x
2. Compare the AIC of both models. Which model is preferred?
3. Now we will apply the function `gls` (from the package `nlme`), see below the R-script. Do the values of the `gls.2` correspond to the values that were obtained through the Bolker approach? To understand the differences, look carefully at 1) the residual standard error of the `gls` (how does this compare to the variance?), 2) the equation of `varPower` (see Zuur), 3) and how the data was generated. To fit the models you can type:

```
library(nlme)
gls.1 = gls(y~x, data=dat,method="ML")
summary(gls.1)
# to specify the variance as a function of x we can use different functions
# (see chapter 4 of Zuur for details) or see ?varClasses
gls.2 = gls(y~x, weights=varPower(form=~x), data=dat,method="ML")
summary(gls.2)
```

```
AIC(gls.1,glis.2)
```

4. The variance estimates are biased because they are estimated with *maximum likelihood* and not *restricted maximum likelihood* (`method=REML` is the default in `gls`). With restricted maximum likelihood you account for the fact that you need estimate the mean from the data. Since the estimated mean will be slightly different than the true mean, the estimated variance is also slightly different from the true variance (i.e. $\sigma^2 = \sum_{i=1}^N (y_i - \mu)^2$). Thus the mean itself is an estimate from the data (i.e. \bar{y}) and not the population parameter itself (i.e. μ). Thus you should fit models with REML when applying AIC. Which model fits the data better?

Fitting models to nested data.

An important assumption of the models we have discussed so far (linear models, generalized linear models and generalized least squares models) is that the observations are independent of each other. This assumption is often violated in ecological data. The solution for the lack of independence is to model the data with so called **mixed effect models**. Mixed effect models contain a fixed part and a random part (see Zuur for more information). To understand how mixed effect models work, we will generate data ourselves and backfit the coefficients with a mixed effect model:

$$Y_{i,j} = \alpha + \beta x + b_i + \epsilon_j$$

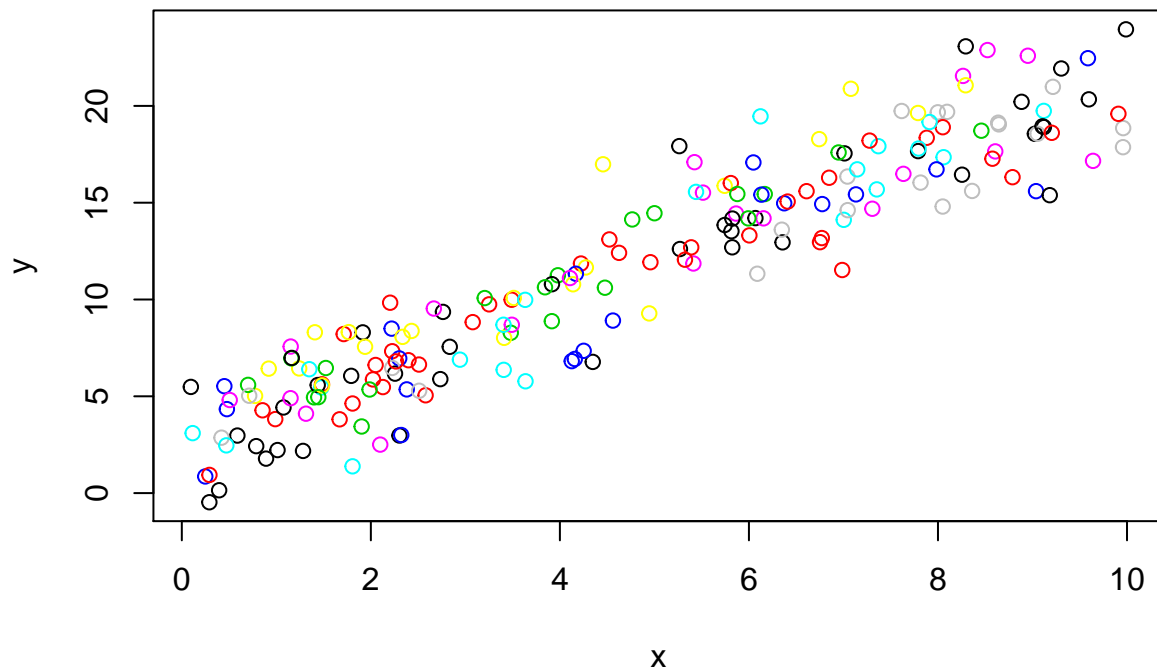
with $b_i \sim N(0, \sigma_{site})$

with $\epsilon_j \sim N(0, \sigma_{res})$

We can simulate data as follows:

```
x = runif(200,0,10) # this is the covariate
sigma_site = 1
site = rnorm(10,0,sigma_site) # we construct 10 different sites
id = as.factor(rep(c(1:10),20)) # site id
sigma_res = 2
y = 2 + 2*x + site[id] + rnorm(200,0,sigma_res)
dat = data.frame(x,y,id)

# let's make a plot
plot(y ~ x, col=id)
```



Now let's fit a mixed effect model with a random intercept across sites:

```
library(nlme)

lme.1 = lme(y ~ x, random=~1|id,data=dat)
summary(lme.1)
```

5. Check the coefficients of the mixed effect model object `lme.1`. Do the values of the random effects make sense? And do the values of the fixed part make sense?

Let's plot the fitted lines for each site:

```
library(ggplot2)
dat$fit.site = fitted(lme.1,level=1)
dat$fit.main = fitted(lme.1,level=0)

ggplot(data=dat) +
  geom_point(aes(x=x,y=y,colour=id))+
  geom_line(aes(x=x,y=fit.site,colour=id))+
  geom_line(aes(x=x,y=fit.main),size=2)
```

6. Simulate data when allowing for random slopes across sites. Choose a σ for the slopes of 1. Fit a mixed effects model with simulated data now allowing for random variation across slopes. Check the book of Zuur for the syntax. If you get convergence problems, run `ctrl <- lmeControl(opt='optim')`, and add `control=ctrl` to the `lme` function, i.e. `lme(y~x...,control=ctrl)`.