Bayesian Hierarchical Models Applied to Accelerometer Data

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Motivation for Heirarchical Models

- Have some data that can be analysed in regression framework (i.e. have response variable + predictors)
- But we have taken several observations from the same individual (e.g. longitudinal study)
- Individuals are different and multiple observations from the same individual are likely to be correlated

How can we analyse such data?
Naive approach: Assign a ‘parameter’ for each individual. But...

- There may be many individuals in the data and not many observations per individual
- Can lead to large number of parameters $\rightarrow$ overfitting, poor generalisation

Motivation for Heirarchical Models

Potential solution - assume that the parameters for individuals are drawn from a 'population' distribution (e.g. normal with some mean and variance).
This is called a mixed, random effects or hierarchical model.

- Reduces 'effective number of parameters'
- Allows for 'borrowing of strength' between similar individuals

Still allows us to do what we wanted in the first place:

- Accounts for between-subject variability and correlation between data from same person.
- In part accounts for important predictors that we don't observe

Motivation of Bayesian Approach

Classical approach for estimating hierarchical models can be problematic:

- Estimation based on likelihood function, not analytically computable for most mixed models.
- Uncertainty of parameter estimates based on asymptotic arguments, not appropriate for small samples.

Bayesian approach advantages:

- Requires no approximations of the model as in classical.
- Proper quantification of uncertainty in parameters and predictions.
- Gain more rich inference about 'random effects' (parameters for different individuals)
- Possible to incorporate 'prior' information in the analysis.

The Bayesian Approach

Treat the parameters of the model as random variables.

- Prior distribution: probability distribution over the parameters prior to data collection.
- Posterior distribution: Combine information about the parameters from the prior and also what we learn about them from the data through the chosen model.

Bayesian algorithms are designed to generate 'samples' from the posterior. All inferences can be based on that sample.

Case study: Accelerometer Data

Purpose was to assess four different methods (called ‘cutpoints’) for classifying activities (e.g. walking, basketball etc) which is based on output from the accelerometer. Response variable is binary (whether or not the method classifies correctly).

12 different activities.

222 different participants with age between 5 and 18 years.

Each participant observed roughly 4 times (roughly 1 year apart).

Case study: Accelerometer Data

Logistic regression model with classification as response and age, classification method and activity as predictors (including interactions)

Need to account for correlation between observations from same individual. Here a random intercept was included for each individual (assumed to be drawn from normal distribution).

Case study: Accelerometer Data