Hands-on training session 3

Hui-Walter models with more than two diagnostic tests

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Introduction

Overview

Date/time:

- 20th February 2020
- 14.00 - 15.30

Teachers:

- Matt Denwood (presenter)
- Giles Innocent
- Sonja Hartnack

Recap

Important points from sessions 1 and 2

Session 3a: Hui-Walter models for multiple tests with conditional indepdendence

What exactly is our latent class?

What do we mean by “conditionally independent?”

Example: three antibody tests

The latent status is actually ‘producing antibodies’ not ‘diseased’

We’re actually pulling **something** out of a hat, and deciding to call it a rabbit

Model specification

If doing this manually, take **extreme** care with multinomial tabulation

Or use autohuiwalter!

- This will also deal gracefully with missing data in one or more test results

Simulating data

Show how to simulate data for arbitrary numbers of test results

Exercise

Simulate data from 3 or 4 tests and analyse

Optional Exercise

Make some data missing for one or more tests and re-generate the model

- Can you see what has changed in the code?

Session 3b: Hui-Walter models for multiple tests with conditional depdendence

Branching of processes leading to test results

Example: two antibody tests and one antigen test

Or three antibody tests where one has a different target to the others

Model specification

Introduce correlations between se and sp

Use autohuiwalter!

Simulating data

Show how to simulate data using an explicit branching process, and correct Se/Sp estimates

[Steal code from ABME course: ABME_hui_walter_complete.R]

Exercise

Simulate data with a dependence between 2 tests

Model assuming conditional independence biases the estimates

Model with conditional depdendence has bigger CI but unbiased

Session 3c: Model selection

Motivation

[Planning for this session to be a general discussion between all instructors and students, as I am not entirely sure what to recommend in terms of model selection - except that I dislike DIC!!!]

Background to DIC

[Some theory slides stolen from ABME course: ABME_Model selection.pptx]

Other methods

DIC works fine for hierarchical normal models

Bayes factors work well if you can count them

WAIC works better for a wide range of models

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* Probably won't work for Hui-Walter though due to lack of independent data
* Could be useful if using the GLM version (untested!)
```

Models tend to be sensitive to priors

Simulating data and testing that your model recovers the parameters is a good idea

Calculating DIC

Add dic and ped to the monitors in runjags

But don't trust the results

Also bear in mind you can't parallelise

Calculating WAIC

Currently a pain - steal code from ABME course:

ABME_waic_example.R

Future Updates

Model criticism will get better in JAGS 5, and the next update of runjags

Installing development version of runjags:

```
# Put on drat server and supply code here
```

WAIC is also calculable from Stan models (easily?)

Discussion and free practical time

What would be useful to add to the autohuiwalter function?

- Modify so it allows Se/Sp priors to be defined as matrices?
- And correlations on/off as matrices?