Posterior prediction for hierarchical models

Stat 340, Fall 2021

We'll build off our ELS math score example here to explore prediction.

Recap: Fitting the hierarchical model in JAGS

First, write the model in a way JAGS understands:

```
modelString <-"
model {

## sampling
for (i in 1:N){
    y[i] ~ dnorm(mu_j[school[i]], invsigma2)
}

## priors
for (j in 1:J){
    mu_j[j] ~ dnorm(mu, invtau2)
}

invsigma2 ~ dgamma(a_s, b_s)
sigma <- sqrt(pow(invsigma2, -1))

## hyperpriors
mu ~ dnorm(mu0, g0)
invtau2 ~ dgamma(a_t, b_t)
tau <- sqrt(pow(invtau2, -1))
}
""</pre>
```

Next, define the data and any initial values for your parameters:

Now, we can use runjags to fit the model via MCMC:

```
posterior <- run.jags(
  modelString,
  n.chains = 1,
  data = the_data,
  monitor = c("mu", "tau", "mu_j", "sigma"),
  adapt = 1000,
  burnin = 5000,
  sample = 5000,
  silent.jags = TRUE
)</pre>
```

Posterior prediction

Suppose we want to make a prediction for school 13, a group that we observed, then we need a posterior predictive distribution

Next, suppose we want to make a **prediction for a school we didn't observe**, let's call it school 101