

HIERARCHICAL MODELS II

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ANNOUNCEMENTS

- Review changes to syllabus.
- Any concerns from the lab meetings?
- Going forward, there will be 5 minute breaks (roughly) halfway through each class meeting.
- Some initial details on final exam.

OUTLINE

- Hierarchical modeling of means recap
- Hierarchical modeling of means and variances
- Gibbs sampler
- ELS data

REGULAR UNIVARIATE NORMAL MODEL

- Recall that if we assume

$$y_i \sim \mathcal{N}(\mu, \sigma^2), \quad i = 1, \dots, n,$$

and set our priors to be

$$\begin{aligned}\pi(\mu) &= \mathcal{N}(\mu_0, \gamma_0^2) \cdot \\ \pi(\sigma^2) &= \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right),\end{aligned}$$

then we have

$$\pi(\mu, \sigma^2 | Y) \propto \left\{ \prod_{i=1}^n p(y_i | \mu, \sigma^2) \right\} \cdot \pi(\mu) \cdot \pi(\sigma^2).$$

FULL CONDITIONALS

- So that

$$\pi(\mu|\sigma^2, Y) = \mathcal{N}(\mu_n, \gamma_n^2).$$

where

$$\gamma_n^2 = \frac{1}{\frac{n}{\sigma^2} + \frac{1}{\gamma_0^2}}; \quad \mu_n = \gamma_n^2 \left[\frac{n}{\sigma^2} \bar{y} + \frac{1}{\gamma_0^2} \mu_0 \right],$$

- and

$$\pi(\sigma^2|\mu, Y) = \mathcal{IG}\left(\frac{\nu_n}{2}, \frac{\nu_n \sigma_n^2}{2}\right),$$

where

$$\nu_n = \nu_0 + n; \quad \sigma_n^2 = \frac{1}{\nu_n} \left[\nu_0 \sigma_0^2 + \sum_{i=1}^n (y_i - \mu)^2 \right].$$

HIERARCHICAL MODELING OF MEANS RECAP

- We've looked at the hierarchical normal model of the form

$$\begin{aligned} y_{ij} | \theta_j, \sigma^2 &\sim \mathcal{N}(\theta_j, \sigma_j^2); \quad i = 1, \dots, n_j \\ \theta_j | \mu, \tau^2 &\sim \mathcal{N}(\mu, \tau^2); \quad j = 1, \dots, J. \end{aligned}$$

- The model gives us an extra hierarchy through the prior on the means, leading to sharing of information across the groups, when estimating the group-specific means.
- As before, first set $\sigma_j^2 = \sigma^2$ for all groups, to simplify posterior inference. We will revisit this today.
- Thus, we only have two variance terms, σ^2 and τ^2 , to inform us on the within-group variation and between-group variation respectively.

HIERARCHICAL NORMAL MODEL RECAP

- Standard semi-conjugate priors as before:

$$\begin{aligned}\pi(\mu) &= \mathcal{N}(\mu_0, \gamma_0^2) \\ \pi(\sigma^2) &= \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right) \\ \pi(\tau^2) &= \mathcal{IG}\left(\frac{\eta_0}{2}, \frac{\eta_0 \tau_0^2}{2}\right).\end{aligned}$$

with

- μ_0 : best guess of average of school averages
- γ_0^2 : set based on plausible ranges of values of μ
- τ_0^2 : best guess of the (scaled) variance of school averages
- η_0 : set based on how tight prior for τ^2 is around τ_0^2
- σ_0^2 : best guess of the (scaled) variance of individual test scores around respective school means
- ν_0 : set based on how tight prior for σ^2 is around σ_0^2 .

POSTERIOR INFERENCE RECAP

- The resulting posterior is therefore:

$$\begin{aligned}\pi(\theta_1, \dots, \theta_J, \mu, \sigma^2, \tau^2 | Y) &\propto p(y | \theta_1, \dots, \theta_J, \mu, \sigma^2, \tau^2) \\ &\quad \times p(\theta_1, \dots, \theta_J | \mu, \sigma^2, \tau^2) \\ &\quad \times \pi(\mu, \sigma^2, \tau^2)\end{aligned}$$

$$\begin{aligned}&= p(y | \theta_1, \dots, \theta_J, \sigma^2) \\ &\quad \times p(\theta_1, \dots, \theta_J | \mu, \tau^2) \\ &\quad \times \pi(\mu) \cdot \pi(\sigma^2) \cdot \pi(\tau^2)\end{aligned}$$

$$\begin{aligned}&= \left\{ \prod_{j=1}^J \prod_{i=1}^{n_j} p(y_{ij} | \theta_j, \sigma^2) \right\} \\ &\quad \times \left\{ \prod_{j=1}^J p(\theta_j | \mu, \tau^2) \right\} \\ &\quad \times \pi(\mu) \cdot \pi(\sigma^2) \cdot \pi(\tau^2)\end{aligned}$$

FULL CONDITIONAL FOR GRAND MEAN

RECAP

- $$\pi(\mu|\theta_1, \dots, \theta_J, \sigma^2, \tau^2, Y) \propto \left\{ \prod_{j=1}^J p(\theta_j|\mu, \tau^2) \right\} \cdot \pi(\mu).$$
- This looks like the full conditional distribution from the one-sample normal case, so that

$$\pi(\mu|\theta_1, \dots, \theta_J, \sigma^2, \tau^2, Y) = \mathcal{N}(\mu_n, \gamma_n^2) \quad \text{where}$$

$$\gamma_n^2 = \frac{1}{\frac{J}{\tau^2} + \frac{1}{\gamma_0^2}}; \quad \mu_n = \gamma_n^2 \left[\frac{J}{\tau^2} \bar{\theta} + \frac{1}{\gamma_0^2} \mu_0 \right]$$

$$\text{and } \bar{\theta} = \frac{1}{J} \sum_{j=1}^J \theta_j.$$

FULL CONDITIONALS FOR GROUP MEANS

RECAP

- $$\pi(\theta_j|\theta_{-j}, \mu, \sigma^2, \tau^2, Y) \propto \left\{ \prod_{i=1}^{n_j} p(y_{ij}|\theta_j, \sigma^2) \right\} \cdot p(\theta_j|\mu, \tau^2)$$
- Those terms include a normal density for θ_j multiplied by a product of normal densities in which θ_j is the mean, again mirroring the one-sample case, so you can show that

$$\pi(\theta_j|\theta_{-j}, \mu, \sigma^2, \tau^2, Y) = \mathcal{N}(\mu_j^*, \tau_j^*) \quad \text{where}$$

$$\tau_j^* = \frac{1}{\frac{n_j}{\sigma^2} + \frac{1}{\tau^2}}; \quad \mu_j^* = \tau_j^* \left[\frac{n_j}{\sigma^2} \bar{y}_j + \frac{1}{\tau^2} \mu \right]$$

FULL CONDITIONALS FOR WITHIN-GROUP VARIANCE RECAP

- $$\pi(\sigma^2 | \theta_1, \dots, \theta_J, \mu, \tau^2, Y) \propto \left\{ \prod_{j=1}^J \prod_{i=1}^{n_j} p(y_{ij} | \theta_j, \sigma^2) \right\} \cdot \pi(\sigma^2)$$
- We can take advantage of the one-sample normal problem, so that our full conditional posterior is

$$\pi(\sigma^2 | \theta_1, \dots, \theta_J, \mu, \tau^2, Y) = \mathcal{IG} \left(\frac{\nu_n}{2}, \frac{\nu_n \sigma_n^2}{2} \right) \quad \text{where}$$

$$\nu_n = \nu_0 + \sum_{j=1}^J n_j; \quad \sigma_n^2 = \frac{1}{\nu_n} \left[\nu_0 \sigma_0^2 + \sum_{j=1}^J \sum_{i=1}^{n_j} (y_{ij} - \theta_j)^2 \right].$$

FULL CONDITIONALS FOR ACROSS-GROUP VARIANCE RECAP

- $$\pi(\tau^2 | \theta_1, \dots, \theta_J, \mu, \sigma^2, Y) \propto \left\{ \prod_{j=1}^J p(\theta_j | \mu, \tau^2) \right\} \cdot \pi(\tau^2)$$

- Again, we have

$$\pi(\tau^2 | \theta_1, \dots, \theta_J, \mu, \sigma^2, Y) = \mathcal{IG} \left(\frac{\eta_n}{2}, \frac{\eta_n \tau_n^2}{2} \right) \quad \text{where}$$

$$\eta_n = \eta_0 + J; \quad \tau_n^2 = \frac{1}{\eta_n} \left[\eta_0 \tau_0^2 + \sum_{j=1}^J (\theta_j - \mu)^2 \right].$$

HIERARCHICAL MODELING OF MEANS AND VARIANCES

- Often researchers emphasize differences in means. However, variances can be very important.
- If we think means vary across groups, why shouldn't we worry about variances also varying across groups?
- In that case, we have the model

$$\begin{aligned} y_{ij} | \theta_j, \sigma_j^2 &\sim \mathcal{N}(\theta_j, \sigma_j^2); \quad i = 1, \dots, n_j \\ \theta_j | \mu, \tau^2 &\sim \mathcal{N}(\mu, \tau^2); \quad j = 1, \dots, J, \end{aligned}$$

- However, now we also need a prior on all the σ_j^2 's that lets us borrow information about across groups.

FULL CONDITIONALS

- Notice that our prior won't affect the full conditions for μ and τ^2 since those have nothing to do with all the σ_j^2 's.
- The full conditional for each θ_j , we have

$$\pi(\theta_j | \theta_{-j}, \mu, \sigma_1^2, \dots, \sigma_J^2, \tau^2, Y) \propto \left\{ \prod_{i=1}^{n_j} p(y_{ij} | \theta_j, \sigma_j^2) \right\} \cdot p(\theta_j | \mu, \tau^2)$$

with the only change from before being σ_j^2 .

- That is, those terms still include a normal density for θ_j multiplied by a product of normals in which θ_j is the mean, again mirroring the previous case, so you can show that

$$\pi(\theta_j | \theta_{-j}, \mu, \sigma_1^2, \dots, \sigma_J^2, \tau^2, Y) = \mathcal{N}(\mu_j^*, \tau_j^*) \quad \text{where}$$

$$\tau_j^* = \frac{1}{\frac{n_j}{\sigma_j^2} + \frac{1}{\tau^2}}; \quad \mu_j^* = \tau_j^* \left[\frac{n_j}{\sigma_j^2} \bar{y}_j + \frac{1}{\tau^2} \mu \right]$$

HOW ABOUT WITHIN-GROUP VARIANCES?

- Now we need to find a semi-conjugate prior for the σ_j^2 's. Before, with one σ^2 , we had

$$\pi(\sigma^2) = \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right),$$

which was nicely semi-conjugate.

- That suggests that maybe we should start with.

$$\sigma_1^2, \dots, \sigma_J^2 | \nu_0, \sigma_0^2 \sim \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right)$$

- However, if we just fix the hyperparameters ν_0 and σ_0^2 in advance, the prior on the σ_j^2 's does not allow borrowing of information across other values of σ_j^2 , to aid in estimation.
- Thus, we actually need to treat ν_0 and σ_0^2 as parameters in a hierarchical model for both means and variances.

HOW ABOUT WITHIN-GROUP VARIANCES?

- Before we get to the choice of the priors for ν_0 and σ_0^2 , we have enough to derive the full conditional for each σ_j^2 . This actually takes a similar form to what we had before we indexed by j , that is,

$$\pi(\sigma_j^2 | \sigma_{-j}^2, \theta_1, \dots, \theta_J, \mu, \tau^2, \nu_0, \sigma_0^2, Y) \propto \left\{ \prod_{i=1}^{n_j} p(y_{ij} | \theta_j, \sigma_j^2) \right\} \cdot \pi(\sigma_j^2 | \nu_0, \sigma_0^2)$$

- This still looks like what we had before, that is, products of normals and one inverse-gamma, so that

$$\pi(\sigma_j^2 | \sigma_{-j}^2, \theta_1, \dots, \theta_J, \mu, \tau^2, \nu_0, \sigma_0^2, Y) = \mathcal{IG} \left(\frac{\nu_j^*}{2}, \frac{\nu_j^* \sigma_j^{2(*)}}{2} \right) \quad \text{where}$$

$$\nu_j^* = \nu_0 + n_j; \quad \sigma_j^{2(*)} = \frac{1}{\nu_j^*} \left[\nu_0 \sigma_0^2 + \sum_{i=1}^{n_j} (y_{ij} - \theta_j)^2 \right].$$

REMAINING HYPER-PRIORS

- Now we can get back to priors for ν_0 and σ_0^2 . Turns out that a semi-conjugate prior for σ_0^2 (see question 2 on homework 2) is a gamma distribution. That is, if we set

$$\pi(\sigma_0^2) = \mathcal{Ga}(a, b),$$

then,

$$\begin{aligned}\pi(\sigma_0^2 | \theta_1, \dots, \theta_J, \sigma_1^2, \dots, \sigma_J^2, \mu, \tau^2, \nu_0, Y) &\propto \left\{ \prod_{j=1}^J p(\sigma_j^2 | \nu_0, \sigma_0^2) \right\} \cdot \pi(\sigma_0^2) \\ &\propto \mathcal{IG}\left(\sigma_j^2; \frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right) \cdot \mathcal{Ga}(\sigma_0^2; a, b)\end{aligned}$$

- Recall that

- $\mathcal{Ga}(y; a, b) \equiv \frac{b^a}{\Gamma(a)} y^{a-1} e^{-by}, \text{ and}$

- $\mathcal{IG}(y; a, b) \equiv \frac{b^a}{\Gamma(a)} y^{-(a+1)} e^{-\frac{b}{y}}.$

REMAINING HYPER-PRIORS

- So $\pi(\sigma_0^2 | \theta_1, \dots, \theta_J, \sigma_1^2, \dots, \sigma_J^2, \mu, \tau^2, \nu_0, Y)$

$$\begin{aligned}
 & \propto \left\{ \prod_{j=1}^J p(\sigma_j^2 | \nu_0, \sigma_0^2) \right\} \cdot \pi(\sigma_0^2) \\
 & \propto \mathcal{IG} \left(\sigma_j^2; \frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2} \right) \cdot \mathcal{Ga}(\sigma_0^2; a, b) \\
 & = \prod_{j=1}^J \frac{\left(\frac{\nu_0 \sigma_0^2}{2} \right)^{\left(\frac{\nu_0}{2} \right)}}{\Gamma \left(\frac{\nu_0}{2} \right)} (\sigma_j^2)^{-\left(\frac{\nu_0}{2} + 1 \right)} e^{-\frac{\nu_0 \sigma_0^2}{2(\sigma_j^2)}} \cdot \left[\frac{b^a}{\Gamma(a)} (\sigma_0^2)^{a-1} e^{-b\sigma_0^2} \right] \\
 & \propto \prod_{j=1}^J (\sigma_0^2)^{\left(\frac{\nu_0}{2} \right)} e^{-\frac{\nu_0 \sigma_0^2}{2(\sigma_j^2)}} \cdot \left[(\sigma_0^2)^{a-1} e^{-b\sigma_0^2} \right] \\
 & \propto (\sigma_0^2)^{\left(\frac{J\nu_0}{2} \right)} e^{-\sigma_0^2 \left[\frac{\nu_0}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right]} \cdot \left[(\sigma_0^2)^{a-1} e^{-b\sigma_0^2} \right]
 \end{aligned}$$

REMAINING HYPER-PRIORS

- That is, the full conditional is

$$\begin{aligned}\pi(\sigma_0^2 | \dots) &\propto \left[(\sigma_0^2)^{\left(\frac{J\nu_0}{2}\right)} e^{-\sigma_0^2 \left[\frac{\nu_0}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2}\right]} \right] \cdot \left[(\sigma_0^2)^{a-1} e^{-b\sigma_0^2} \right] \\ &\propto \left[(\sigma_0^2)^{\left(a + \frac{J\nu_0}{2} - 1\right)} e^{-\sigma_0^2 \left[b + \frac{\nu_0}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2}\right]} \right] \\ &\equiv \mathcal{Ga}(\sigma_0^2; a_n, b_n),\end{aligned}$$

where

$$a_n = a + \frac{J\nu_0}{2}; \quad b_n = b + \frac{\nu_0}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2}.$$

REMAINING HYPER-PRIORS

- Ok that leaves us with one parameter to go, i.e., ν_0 . Turns out there is no simple conjugate/semi-conjugate prior for ν_0 .
- Common practice is to restrict ν_0 to be an integer (which makes sense when we think of it as being degrees of freedom, which also means it cannot be zero). With the restriction, we need a discrete distribution as the prior with support on $\nu_0 = 1, 2, 3, \dots$
- **Poll question: Can we use either a binomial or a Poisson prior on for ν_0 ?**
- A popular choice is the geometric distribution with pmf $p(\nu_0) = (1 - p)^{\nu_0 - 1} p$.
- However, we will rewrite the kernel as $\pi(\nu_0) \propto e^{-\alpha \nu_0}$. How did we get here from the geometric pmf and what is α ?

FINAL FULL CONDITIONAL

- With this prior, $\pi(\nu_0 | \theta_1, \dots, \theta_J, \sigma_1^2, \dots, \sigma_J^2, \mu, \tau^2, \sigma_0^2, Y)$

$$\begin{aligned}
 &\propto \left\{ \prod_{j=1}^J p(\sigma_j^2 | \nu_0, \sigma_0^2) \right\} \cdot \pi(\nu_0) \\
 &\propto \mathcal{IG} \left(\sigma_j^2; \frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2} \right) \cdot e^{-\alpha \nu_0} \\
 &= \left[\prod_{j=1}^J \frac{\left(\frac{\nu_0 \sigma_0^2}{2} \right)^{\left(\frac{\nu_0}{2} \right)}}{\Gamma \left(\frac{\nu_0}{2} \right)} (\sigma_j^2)^{-\left(\frac{\nu_0}{2} + 1 \right)} e^{-\frac{\nu_0 \sigma_0^2}{2(\sigma_j^2)}} \right] \cdot e^{-\alpha \nu_0} \\
 &\propto \left[\left(\frac{\left(\frac{\nu_0 \sigma_0^2}{2} \right)^{\left(\frac{\nu_0}{2} \right)}}{\Gamma \left(\frac{\nu_0}{2} \right)} \right)^J \cdot \left(\prod_{j=1}^J \frac{1}{\sigma_j^2} \right)^{\left(\frac{\nu_0}{2} - 1 \right)} \cdot e^{-\nu_0 \left[\frac{\sigma_0^2}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right]} \right] \cdot e^{-\alpha \nu_0}
 \end{aligned}$$

FINAL FULL CONDITIONAL

- That is, the full conditional is

$$\pi(\nu_0 | \dots) \propto \left[\left(\frac{\left(\frac{\nu_0 \sigma_0^2}{2} \right)^{\left(\frac{\nu_0}{2} \right)}}{\Gamma\left(\frac{\nu_0}{2}\right)} \right)^J \cdot \left(\prod_{j=1}^J \frac{1}{\sigma_j^2} \right)^{\left(\frac{\nu_0}{2} - 1 \right)} \cdot e^{-\nu_0 \left[\alpha + \frac{\sigma_0^2}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right]} \right],$$

which is not a known kernel and is thus unnormalized (i.e., does not integrate to 1 in its current form).

- This sure looks like a lot, but it will be relatively easy to compute in R.
- Now, technically, the support is $\nu_0 = 1, 2, 3, \dots$, however, we can compute this to compute the unnormalized distribution across a grid of ν_0 values, say, $\nu_0 = 1, 2, 3, \dots$ for some large K , and then sample.

FINAL FULL CONDITIONAL

- One more thing, computing these probabilities on the raw scale can be problematic particularly because of the product inside. Good idea to transform to the log scale instead.
- That is,

$$\pi(\nu_0 | \dots) \propto \left[\left(\frac{\left(\frac{\nu_0 \sigma_0^2}{2} \right)^{\left(\frac{\nu_0}{2} \right)^J}}{\Gamma\left(\frac{\nu_0}{2}\right)} \right) \cdot \left(\prod_{j=1}^J \frac{1}{\sigma_j^2} \right)^{\left(\frac{\nu_0}{2} - 1 \right)} \cdot e^{-\nu_0 \left[\alpha + \frac{\sigma_0^2}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right]} \right]$$

$$\begin{aligned} \Rightarrow \ln \pi(\nu_0 | \dots) &\propto \left(\frac{J\nu_0}{2} \right) \ln \left(\frac{\nu_0 \sigma_0^2}{2} \right) - J \ln \left[\Gamma\left(\frac{\nu_0}{2}\right) \right] \\ &\quad + \left(\frac{\nu_0}{2} - 1 \right) \left(\sum_{j=1}^J \ln \left[\frac{1}{\sigma_j^2} \right] \right) \\ &\quad - \nu_0 \left[\alpha + \frac{\sigma_0^2}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right] \end{aligned}$$

ELS DATA

- Finally, enough math and some data!
- We have data from the 2002 Educational Longitudinal Survey (ELS). This survey includes a random sample of 100 large urban public high schools, and 10th graders randomly sampled within these high schools.

```
Y <- as.matrix(dget("http://www2.stat.duke.edu/~pdh10/FCBS/Inline/Y.school.mathscore"))  
dim(Y)
```

```
## [1] 1993      2
```

```
head(Y)
```

```
##      school mathscore  
## [1,]      1    52.11  
## [2,]      1    57.65  
## [3,]      1    66.44  
## [4,]      1    44.68  
## [5,]      1    40.57  
## [6,]      1    35.04
```

```
length(unique(Y[, "school"]))
```

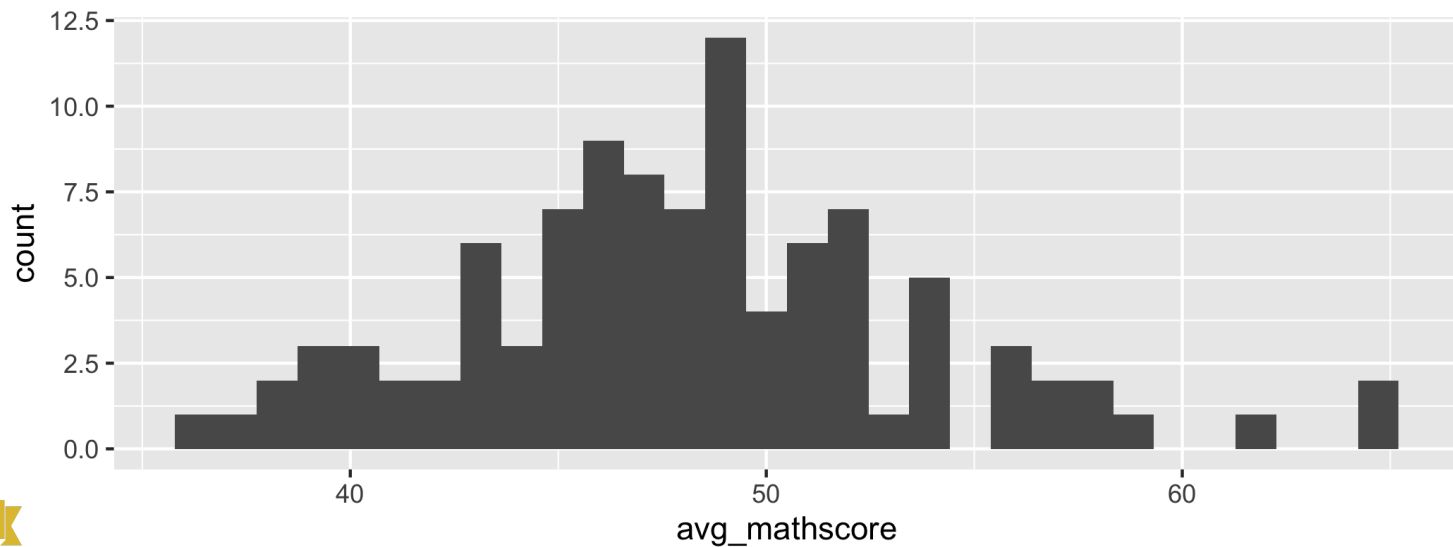
```
## [1] 100
```

ELS DATA

First, some EDA:

```
Data <- as.data.frame(Y)
Data$school <- as.factor(Data$school)
Data %>%
  group_by(school) %>%
  na.omit() %>%
  summarise(avg_mathscore = mean(mathscore)) %>%
  dplyr::ungroup() %>%
  ggplot(aes(x = avg_mathscore)) +
  geom_histogram()
```

`stat_bin()` using `bins = 30`. Pick better value with `binwidth`.

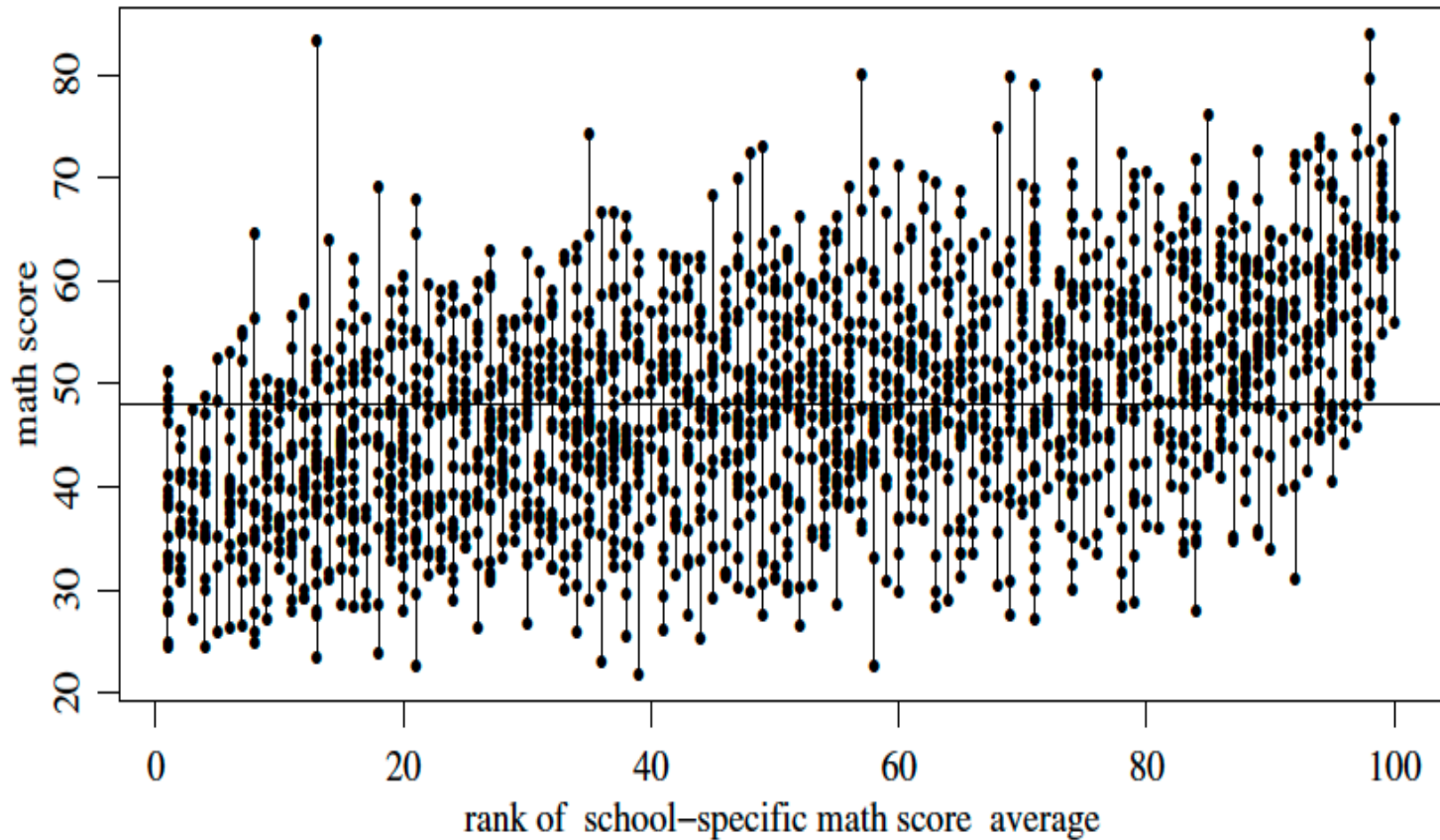


ELS DATA

There does appear to be school-related differences in means and in variances, some of which are actually related to the sample sizes.

ELS DATA

Consider the math scores of these children:



ELS HYPOTHESES

- Investigators may be interested in the following:
 - Differences in mean scores across schools
 - Differences in school-specific variances
- How do we evaluate these questions in a statistical model?

HIERARCHICAL MODEL

- We can write out the full model we've been describing as follows.

$$y_{ij}|\theta_j, \sigma_j^2 \sim \mathcal{N}(\theta_j, \sigma_j^2); \quad i = 1, \dots, n_j$$

$$\theta_j|\mu, \tau^2 \sim \mathcal{N}(\mu, \tau^2); \quad j = 1, \dots, J$$

$$\sigma_1^2, \dots, \sigma_J^2|\nu_0, \sigma_0^2 \sim \mathcal{IG}\left(\frac{\nu_0}{2}, \frac{\nu_0 \sigma_0^2}{2}\right)$$

$$\mu \sim \mathcal{N}(\mu_0, \gamma_0^2)$$

$$\tau^2 \sim \mathcal{IG}\left(\frac{\eta_0}{2}, \frac{\eta_0 \tau_0^2}{2}\right).$$

$$\pi(\nu_0) \propto e^{-\alpha \nu_0}$$

$$\sigma_0^2 \sim \mathcal{Ga}(a, b).$$

- Now, we need to specify hyperparameters. That should be fun!

PRIOR SPECIFICATION

- This exam was designed to have a national mean of 50 and standard deviation of 10. Suppose we don't have any other information.
- Then, we can specify

$$\mu \sim \mathcal{N}(\mu_0 = 50, \gamma_0^2 = 25)$$

$$\tau^2 \sim \mathcal{IG}\left(\frac{\eta_0}{2} = \frac{1}{2}, \frac{\eta_0 \tau_0^2}{2} = \frac{100}{2}\right).$$

$$\pi(\nu_0) \propto e^{-\alpha \nu_0} \propto e^{-\nu_0}$$

$$\sigma_0^2 \sim \mathcal{Ga}\left(a = 1, b = \frac{1}{100}\right).$$

- Are these prior distributions overly informative?

FULL CONDITIONALS (RECAP)

$$\pi(\theta_j | \dots) = \mathcal{N}(\mu_j^*, \tau_j^*) \quad \text{where}$$

- $$\tau_j^* = \frac{1}{\frac{n_j}{\sigma_j^2} + \frac{1}{\tau^2}}; \quad \mu_j^* = \tau_j^* \left[\frac{n_j}{\sigma_j^2} \bar{y}_j + \frac{1}{\tau^2} \mu \right]$$

$$\pi(\sigma_j^2 | \dots) = \mathcal{IG}\left(\frac{\nu_j^*}{2}, \frac{\nu_j^* \sigma_j^{2(*)}}{2}\right) \quad \text{where}$$

- $$\nu_j^* = \nu_0 + n_j; \quad \sigma_j^{2(*)} = \frac{1}{\nu_j^*} \left[\nu_0 \sigma_0^2 + \sum_{i=1}^{n_j} (y_{ij} - \theta_j)^2 \right].$$

$$\pi(\mu | \dots) = \mathcal{N}(\mu_n, \gamma_n^2) \quad \text{where}$$

- $$\gamma_n^2 = \frac{1}{\frac{J}{\tau^2} + \frac{1}{\gamma_0^2}}; \quad \mu_n = \gamma_n^2 \left[\frac{J}{\tau^2} \bar{\theta} + \frac{1}{\gamma_0^2} \mu_0 \right]$$

FULL CONDITIONALS (RECAP)

$$\pi(\tau^2 | \dots) = \mathcal{IG} \left(\frac{\eta_n}{2}, \frac{\eta_n \tau_n^2}{2} \right) \quad \text{where}$$

■

$$\eta_n = \eta_0 + J; \quad \tau_n^2 = \frac{1}{\eta_n} \left[\eta_0 \tau_0^2 + \sum_{j=1}^J (\theta_j - \mu)^2 \right].$$

$$\begin{aligned} \ln \pi(\nu_0 | \dots) &\propto \left(\frac{J\nu_0}{2} \right) \ln \left(\frac{\nu_0 \sigma_0^2}{2} \right) - J \ln \left[\Gamma \left(\frac{\nu_0}{2} \right) \right] \\ &\quad + \left(\frac{\nu_0}{2} - 1 \right) \left(\sum_{j=1}^J \ln \left[\frac{1}{\sigma_j^2} \right] \right) \\ &\quad - \nu_0 \left[\alpha + \frac{\sigma_0^2}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2} \right] \end{aligned}$$

■

$$\pi(\sigma_0^2 | \dots) = \mathcal{Ga}(\sigma_0^2; a_n, b_n) \quad \text{where}$$

■

$$a_n = a + \frac{J\nu_0}{2}; \quad b_n = b + \frac{\nu_0}{2} \sum_{j=1}^J \frac{1}{\sigma_j^2}.$$

SIDE NOTES

- Obviously, as you have seen in the lab, we can simply use Stan (or JAGS, BUGS) to fit these models without needing to do any of this ourselves.
- The point here (as you should already know by now) is to learn and understand all the details, including the math!

GIBBS SAMPLER

```
#Data summaries
J <- length(unique(Y[, "school"]))
ybar <- c(by(Y[, "mathscore"], Y[, "school"], mean))
s_j_sq <- c(by(Y[, "mathscore"], Y[, "school"], var))
n <- c(table(Y[, "school"]))

#Hyperparameters for the priors
mu_0 <- 50
gamma_0_sq <- 25
eta_0 <- 1
tau_0_sq <- 100
alpha <- 1
a <- 1
b <- 1/100

#Grid values for sampling nu_0_grid
nu_0_grid <- 1:5000

#Initial values for Gibbs sampler
theta <- ybar
sigma_sq <- s_j_sq
mu <- mean(theta)
tau_sq <- var(theta)
nu_0 <- 1
sigma_0_sq <- 100
```

GIBBS SAMPLER

```
#first set number of iterations and burn-in, then set seed
n_iter <- 10000; burn_in <- 0.3*n_iter
set.seed(1234)

#Set null matrices to save samples
SIGMA_SQ <- THETA <- matrix(nrow=n_iter, ncol=J)
OTHER_PAR <- matrix(nrow=n_iter, ncol=4)

#Now, to the Gibbs sampler
for(s in 1:(n_iter+burn_in)){

  #update the theta vector (all the theta_j's)
  tau_j_star <- 1/(n/sigma_sq + 1/tau_sq)
  mu_j_star <- tau_j_star*(ybar*n/sigma_sq + mu/tau_sq)
  theta <- rnorm(J,mu_j_star,sqrt(tau_j_star))

  #update the sigma_sq vector (all the sigma_sq_j's)
  nu_j_star <- nu_0 + n
  theta_long <- rep(theta,n)
  nu_j_star_sigma_j_sq_star <-
    nu_0*sigma_0_sq + c(by((Y[, "mathscore"] - theta_long)^2, Y[, "school"], sum))
  sigma_sq <- 1/rgamma(J, (nu_j_star/2), (nu_j_star_sigma_j_sq_star/2))

  #update mu
  gamma_n_sq <- 1/(J/tau_sq + 1/gamma_0_sq)
  mu_n <- gamma_n_sq*(J*mean(theta)/tau_sq + mu_0/gamma_0_sq)
  mu <- rnorm(1,mu_n,sqrt(gamma_n_sq))
}
```

GIBBS SAMPLER

```
#update tau_sq
eta_n <- eta_0 + J
eta_n_tau_n_sq <- eta_0*tau_0_sq + sum((theta-mu)^2)
tau_sq <- 1/rgamma(1,eta_n/2,eta_n_tau_n_sq/2)

#update sigma_0_sq
sigma_0_sq <- rgamma(1,(a + J*nu_0/2),(b + nu_0*sum(1/sigma_sq)/2))

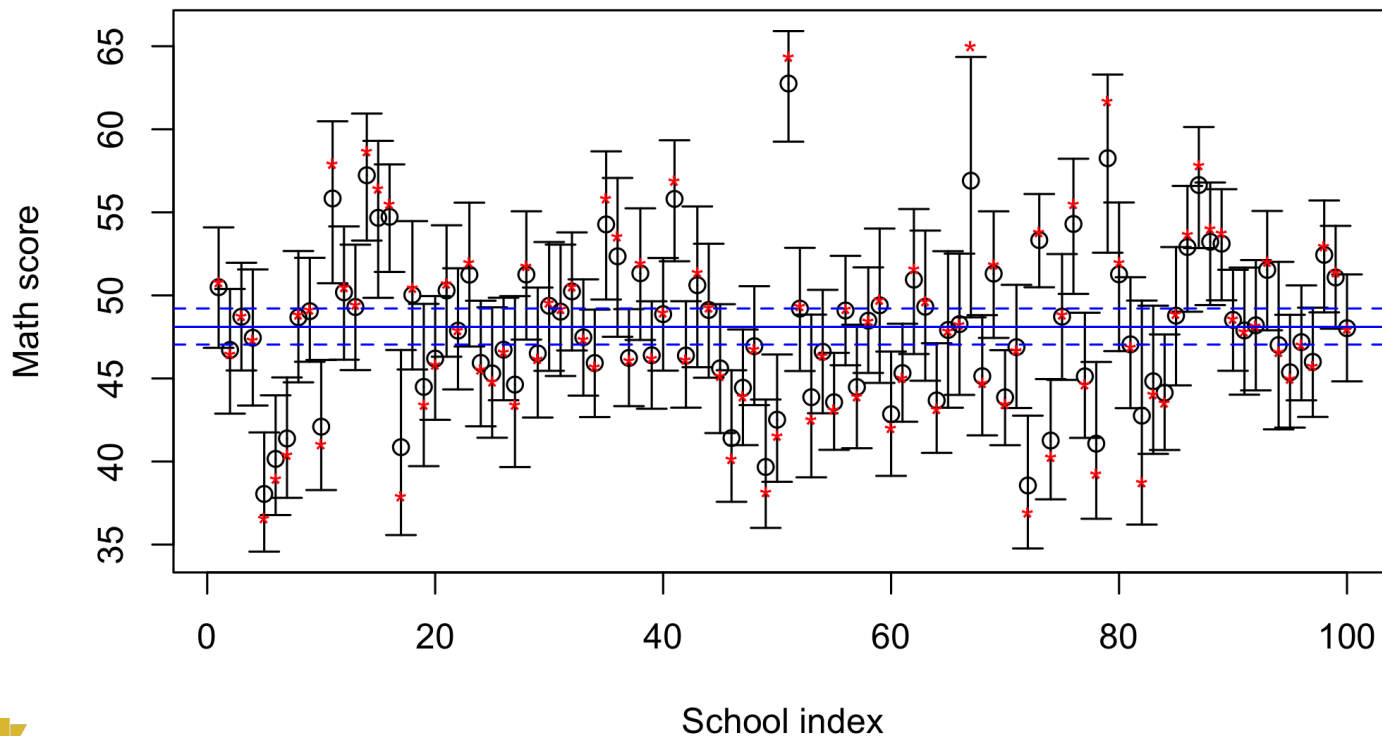
#update nu_0
log_prob_nu_0 <- (J*nu_0_grid/2)*log(nu_0_grid*sigma_0_sq/2) -
  J*lgamma(nu_0_grid/2) +
  (nu_0_grid/2-1)*sum(log(1/sigma_sq)) -
  nu_0_grid*(alpha + sigma_0_sq*sum(1/sigma_sq)/2)
nu_0 <- sample(nu_0_grid,1, prob = exp(log_prob_nu_0 - max(log_prob_nu_0)) )
#this last step substracts the maximum logarithm from all logs
#it is a neat trick that throws away all results that are so negative
#they will screw up the exponential
#note that the sample function will renormalize the probabilities internally

#save results only past burn-in
if(s > burn_in){
  THETA[(s-burn_in),] <- theta
  SIGMA_SQ[(s-burn_in),] <- sigma_sq
  OTHER_PAR[(s-burn_in),] <- c(mu,tau_sq,sigma_0_sq,nu_0)
}
}
colnames(OTHER_PAR) <- c("mu","tau_sq","sigma_0_sq","nu_0")
```

POSTERIOR INFERENCE

The blue lines indicate the posterior median and a 95% for μ . The red asterisks indicate the data values \bar{y}_j .

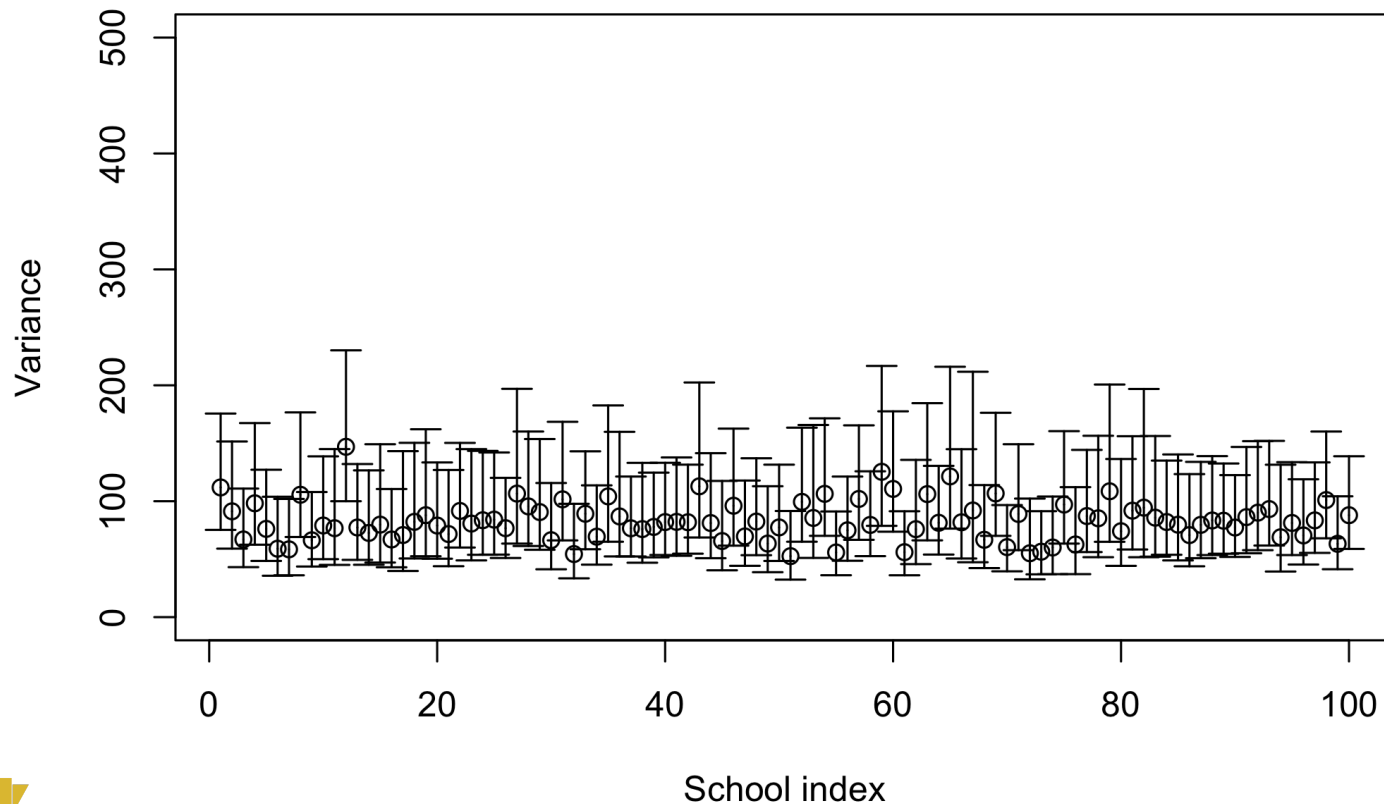
Posterior medians and 95% CI for schools



POSTERIOR INFERENCE

Posterior summaries of σ_j^2 .

Posterior medians and 95% CI for schools



POSTERIOR INFERENCE

Shrinkage as a function of sample size.

##	n	Sample group mean	Post. est. of group mean	Post. est. of overall mean
## 1	31	50.81355	50.49363	48.10549
## 2	22	46.47955	46.71544	48.10549
## 3	23	48.77696	48.71578	48.10549
## 4	19	47.31632	47.44935	48.10549
## 5	21	36.58286	38.04669	48.10549

##	n	Sample group mean	Post. est. of group mean	Post. est. of overall mean
## 15	12	56.43083	54.67213	48.10549
## 16	23	55.49609	54.72904	48.10549
## 17	7	37.92714	40.86290	48.10549
## 18	14	50.45357	50.03007	48.10549

##	n	Sample group mean	Post. est. of group mean	Post. est. of overall mean
## 67	4	65.01750	56.90436	48.10549
## 68	19	44.74684	45.13522	48.10549
## 69	24	51.86917	51.31079	48.10549
## 70	27	43.47037	43.86470	48.10549
## 71	22	46.70455	46.88374	48.10549
## 72	13	36.95000	38.55704	48.10549

HOW ABOUT NON-NORMAL MODELS?

- Suppose we have $y_{ij} \in \{0, 1, \dots\}$ being a count for subject i in group j .
- For count data, it is natural to use a Poisson likelihood, that is,

$$y_{ij} \sim \text{Poisson}(\theta_j)$$

where each $\theta_j = \mathbb{E}[y_{ij}]$ is a group specific mean.

- When there are limited data within each group, it is natural to borrow information.
- How can we accomplish this with a hierarchical model?
- See homework 6 for a similar setup!