

# Lecture 11 - Key

## Hierarchical Regression

Recall the hierarchical normal model we used previously.

This model allowed a different mean for each group (school), denoted  $\theta_j$ .

Now returning to the motivating example, test scores within a school. Suppose there are other factors that affect test scores at the school, specifically how about the socio-economic standing of families in that school district.

We can now write the model as:

where  $\tilde{x}_j$  is a vector of socio-economic information about school  $j$ , this could also include 1 to account for an intercept.

What priors do we need to fit this model?

Similar to the hierarchical means model, we can obtain full conditional distributions for  $\sigma^2$ ,  $\Sigma_0$ ,  $\tilde{\theta}$ , and  $\tilde{\mu}$ . This allows us to use a Gibbs sampler to draw samples from the joint posterior distribution.

## Exercise

1. Write out the model for a hierarchical regression setting. To keep it simple assume we are fitting a different intercept and slope (associated with square footage) for the different zip codes.

The following priors are specified for this setting.

## Extract Data

```
library(readr)
library(dplyr)
library(tidyr)
seattle <- read_csv('http://www.math.montana.edu/ahoegh/teaching/stat532/data/SeattleHousing.csv')
set.seed(11122018)

num.zips <- 10
num.houses <- 20
keep.zips <- sample(unique(seattle$zipcode), num.zips)

seattle.filter <- seattle %>% filter(zipcode %in% keep.zips) %>% group_by(zipcode) %>%
  sample_n(num.houses) %>% arrange(zipcode) %>% select(price, sqft_living, zipcode, id) %>%
  ungroup() %>% mutate(zipcode = as.factor(zipcode), house.num = rep(1:num.houses, num.zips))

price.wide <- seattle.filter %>% select(zipcode, price, house.num) %>%
  spread(key = zipcode, value = price) %>% select(-house.num)

size.wide <- seattle.filter %>% select(zipcode, sqft_living, house.num) %>%
  spread(key = zipcode, value = sqft_living) %>% select(-house.num)

library(ggplot2)
ggplot(data = seattle.filter, aes(y = price, x = sqft_living)) + geom_point() +
  geom_smooth() + facet_wrap(~zipcode, nrow = 5, ncol = 2)
```

2. Compare and contrast the following two models

```
summary(lm(price ~ sqft_living , data = seattle.filter))
```

```
library(rjags)
modelstring <- "
model {
  # Model
  for (zip in 1:num.zips) {
    for (house in 1:num.houses) {
      mu[house, zip] <- alpha + beta * (x[house,zip]);
      price.wide[house,zip] ~ dnorm(mu[house,zip], tau.price)
    }
  }
  # Priors
  alpha ~ dnorm(0, 1/1e16);
  beta ~ dnorm(0, 1/1e16);
  tau.price ~ dgamma(.0001, .0001);

  # Transformations
  sigma.price <- 1.0/sqrt(tau.price);
}
"
writeLines(modelstring, "model.txt")

Data <- list(
  num.zips = num.zips,
  num.houses = num.houses,
  price.wide = price.wide,
  x = size.wide)
mod1 <- jags.model("model.txt", data=Data, n.chains=4, n.adapt=1000)

codaSamples = coda.samples( mod1 , variable.names=c("alpha","beta", 'sigma.price') ,
                             n.iter=10000)

summary(codaSamples)
```

3. Now again, compare and contrast the following two models.

```
summary(lm(price~ sqft_living + zipcode - 1, data = seattle.filter))
```

```
library(rjags)
modelstring <- "
model {
  # Model
  for (zip in 1:num.zips) {
    for (house in 1:num.houses) {
      mu[house, zip] <- alpha[zip] + beta * (x[house,zip]);
      price.wide[house,zip] ~ dnorm(mu[house,zip], tau.price)
    }
    alpha[zip] ~ dnorm(alpha.mu, alpha.tau);
  }
  # Priors
  alpha.mu ~ dnorm(0, 1/1e16);
  beta ~ dnorm(0, 1/1e16);
  tau.price ~ dgamma(.0001, .0001);
  alpha.tau ~ dgamma(.00001, .00001);
  # Transformations
  alpha.sigma <- 1.0/sqrt(alpha.tau);
  sigma.price <- 1.0/sqrt(tau.price);
}
"
writeLines(modelstring, "model.txt")

Data <- list(
  num.zips = num.zips,
  num.houses = num.houses,
  price.wide = price.wide,
  x = size.wide)
mod1 <- jags.model("model.txt", data=Data, n.chains=4, n.adapt=1000)

codaSamples = coda.samples( mod1 , variable.names=c("alpha","beta", 'sigma.price', 'alpha.mu') ,
  n.iter=10000)

summary(codaSamples)
```