

# STA 360/602L: MODULE 3.9

## MCMC AND GIBBS SAMPLING III

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# RECAP OF NORMAL MODEL

- Sampling model:

$$y_i | \mu, \tau \stackrel{iid}{\sim} \mathcal{N}(\mu, \tau^{-1}).$$

- Suppose we want to specify our uncertainties about  $\mu$  and  $\tau$  independently of each other. That is, we want  $\pi(\mu, \tau) = \pi(\mu)\pi(\tau)$ .
- For example,

$$\begin{aligned}\mu &\sim \mathcal{N}(\mu_0, \sigma_0^2). \\ \tau &\sim \text{Gamma}\left(\frac{\nu_0}{2}, \frac{\nu_0}{2\tau_0}\right).\end{aligned}$$

- Then in this form, where  $\sigma_0^2$  is not proportional to  $\frac{1}{\tau}$ , the marginal density of  $\tau$  is not a gamma density (or a density we can easily sample from).
- We need to do **Gibbs sampling**.

# FULL CONDITIONALS

- That is, we need

$$\mu|Y, \tau \sim \mathcal{N}(\mu_n, \tau_n^{-1}),$$

where

$$\mu_n = \frac{\frac{\mu_0}{\sigma_0^2} + n\tau\bar{y}}{\frac{1}{\sigma_0^2} + n\tau}$$

$$\tau_n = \frac{1}{\sigma_0^2} + n\tau.$$

# FULL CONDITIONALS

- and

$$\tau|\mu, Y \sim \text{Gamma} \left( \frac{\nu_n}{2}, \frac{\nu_n \sigma_n^2(\mu)}{2} \right),$$

where

$$\nu_n = \nu_0 + n$$

$$\sigma_n^2(\mu) = \frac{1}{\nu_n} \left[ \frac{\nu_0}{\tau_0} + \sum_{i=1}^n (y_i - \mu)^2 \right] = \frac{1}{\nu_n} \left[ \frac{\nu_0}{\tau_0} + n s_n^2(\mu) \right]$$

with  $s_n^2(\mu) = \frac{1}{n} \sum_{i=1}^n (y_i - \mu)^2 \Rightarrow n s_n^2(\mu) = (n-1) s^2 + n(\bar{y} - \mu)^2.$

# RECALL THE PYGMALION DATA

- Let's implement this Gibbs sampler for the Pygmalion data.
- For now, let's focus only on the accelerated group.
- Data for accelerated group (A): 20, 10, 19, 15, 9, 18.
- Summary statistics:  $\bar{y}_A = 15.2$ ;  $s_A = 4.71$ .

# RECALL THE PYGMALION DATA

- Suppose we assume, as we did before, that these improvement scores are normal with mean  $\mu$  and variance  $\frac{1}{\tau}$ .
- As a reminder, in the conjugate case, we had

$$\tau \sim \text{Gamma} \left( \frac{\nu_0}{2}, \frac{\nu_0}{2\tau_0} \right)$$
$$\mu|\tau \sim \mathcal{N} \left( \mu_0, \frac{1}{\kappa_0\tau} \right).$$

- We set
  - $\mu_0 = 0$ , to reflect "no idea whether students would improve IQ on average";
  - $\kappa_0 = 1$ , to reflect "little faith in this belief, equivalent to having only 1 prior observation in each group";
  - $\nu_0 = 1$  and  $1/\tau_0 = 100$ , based on literature, that is, SD of change scores should be around 10.

# RECALL THE PYGMALION DATA

- Now, in the non-conjugate case, we have

$$\begin{aligned}\mu &\sim \mathcal{N}(\mu_0, \sigma_0^2). \\ \tau &\sim \text{Gamma}\left(\frac{\nu_0}{2}, \frac{\nu_0}{2\tau_0}\right).\end{aligned}$$

- Suppose for  $\mu$ , we use a  $\mathcal{N}(0, 100)$  prior, and for  $\tau$  we use a  $\text{Ga}(\frac{1}{2}, 50)$  prior.
- Matching with

$$\begin{aligned}\mu &\sim \mathcal{N}(\mu_0, \sigma_0^2). \\ \tau &\sim \text{Gamma}\left(\frac{\nu_0}{2}, \frac{\nu_0}{2\tau_0}\right),\end{aligned}$$

we have:  $\mu_0 = 0$ ,  $\sigma_0^2 = 100$ ,  $\nu_0 = 1$  and  $\tau_0 = 1/100$ .

# GIBBS SAMPLING FOR PYGMALION DATA

```
y <- c(20,10,19,15,9,18) #data
y_bar <- mean(y); s2 <- var(y); n <- length(y) #sample statistics you'll need

S <- 10000 # number of samples to draw

PHI <- matrix(nrow=S,ncol=3); #matrix to save results
colnames(PHI) <- c("mu","tau","sigma2")
PHI[1,] <- phi <- c(y_bar,1/s2,s2) #starting values are MLEs

mu0 <- 0; sigma02 <- 100; nu0 <- 1; tau0 <- 1/100 #hyperparameters

##### Gibbs sampler #####
set.seed(1234) #to replicate results exactly
for(s in 2:S) {
#first, draw new mu
taun <- 1/sigma02 + n*phi[2]
mun <- (mu0/sigma02 + n*y_bar*phi[2])/taun
phi[1] <- rnorm(1,mun,sqrt(1/taun))

#now, draw new tau/sigma2
nun <- nu0+n
#trick to speed up calculation of sum(y_i-\mu)^2
s2nmu <- (nu0/tau0 + (n-1)*s2 + n*(y_bar-phi[1])^2)/nun
phi[2] <- rgamma(1,nun/2,nun*s2nmu/2)
phi[3] <- 1/phi[2] #save sigma2

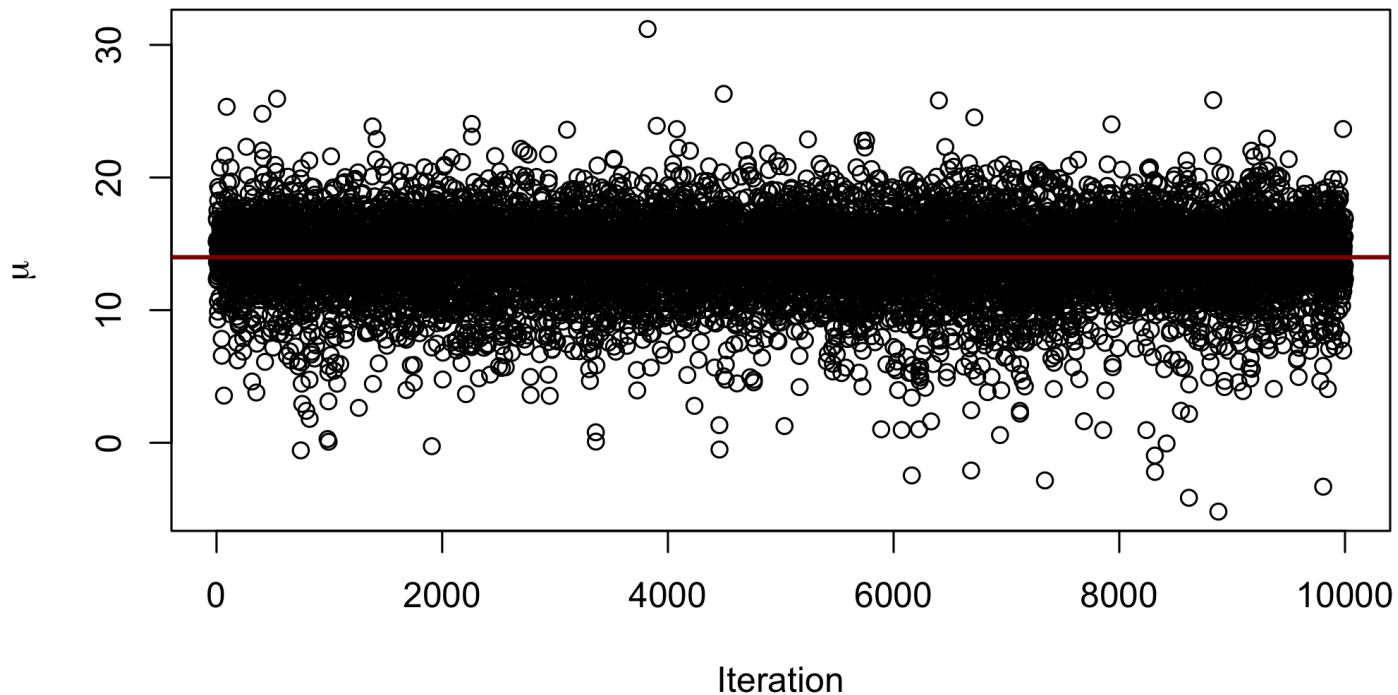
#save the current joint draws
PHI[s,] <- phi
}
##### End of Gibbs sampler #####
```



# PYGMALION DATA: MEAN

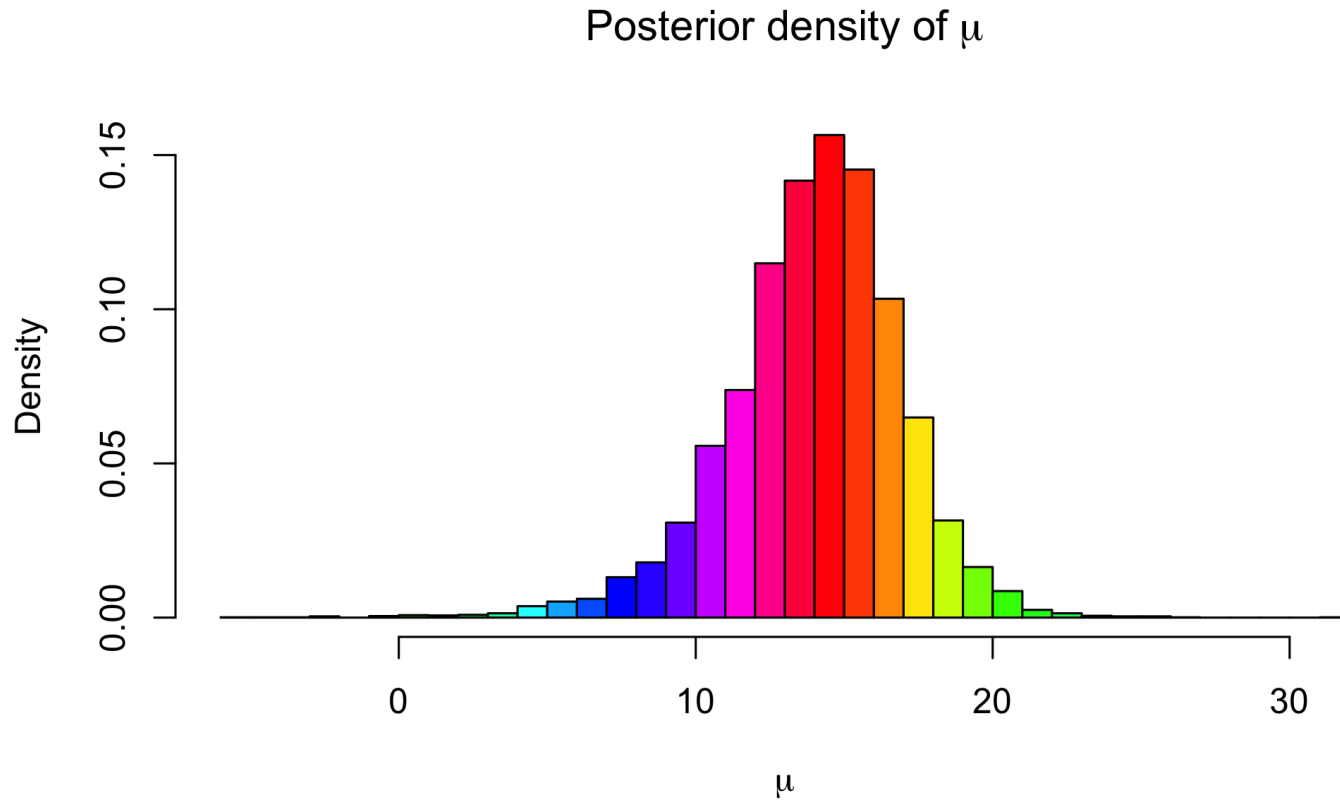
```
plot(PHI[,1],ylab=expression(mu),xlab="Iteration",  
     main=expression(paste("Sampled values of ",mu)))  
abline(a=mean(PHI[,1]),b=0,col="red4",lwd=2)
```

Sampled values of  $\mu$



# PYGMALION DATA: MEAN

```
hist(PHI[,1],col=rainbow(20),xlab=expression(mu),ylab="Density",freq=F,breaks=50,  
main=expression(paste("Posterior density of ",mu)))
```



# PYGMALION DATA: MEAN

```
round(mean(PHI[,1]),3)
```

```
## [1] 13.99
```

```
round(quantile(PHI[,1],c(0.025,0.5,0.975)),3)
```

```
## 2.5% 50% 97.5%  
## 7.520 14.217 19.277
```

Posterior summaries for  $\mu$ :

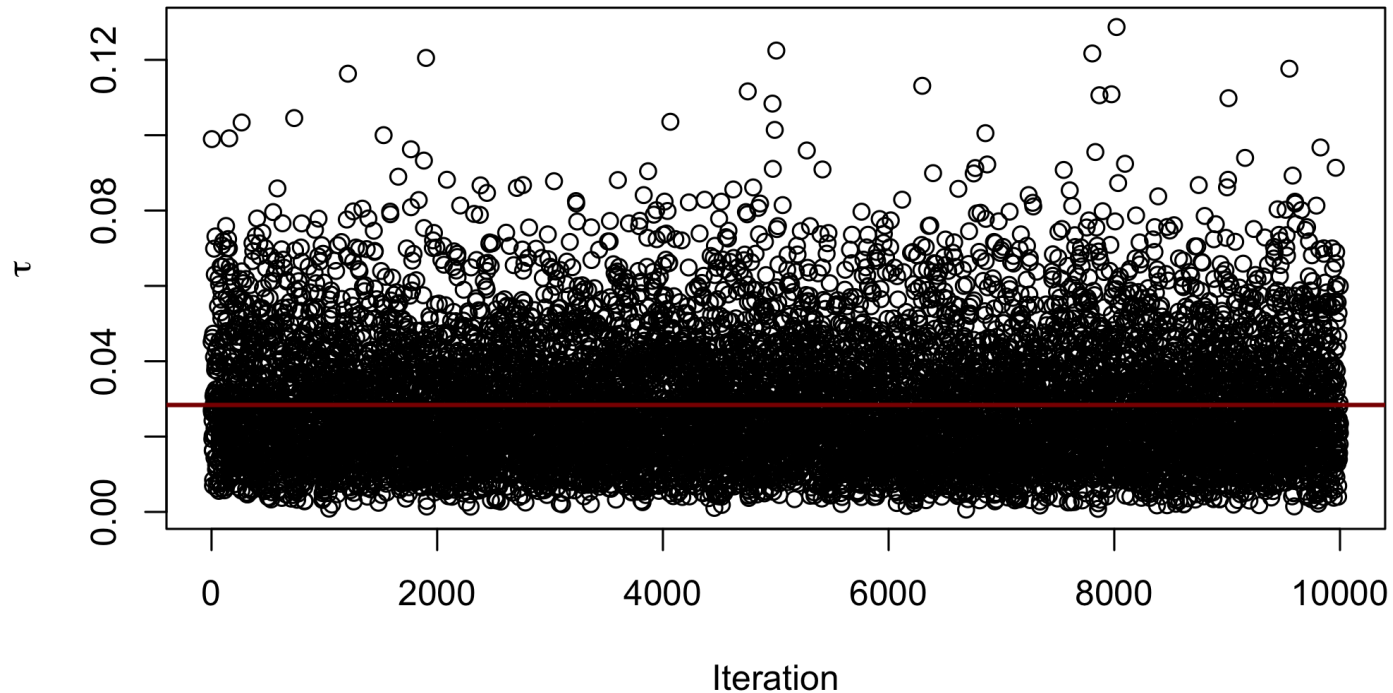
- Posterior mean  $\approx 14$ .
- Posterior median  $\approx 14.22$ .
- 95% credible interval  $\approx (7.52, 19.28)$ .

For context,  $\bar{y}_A = 15.2$ , and we used a  $\mathcal{N}(0, 100)$  prior for  $\mu$ .

# PYGMALION DATA: PRECISION

```
plot(PHI[,2],ylab=expression(tau),xlab="Iteration",  
     main=expression(paste("Sampled values of ",tau)))  
abline(a=mean(PHI[,2]),b=0,col="red4",lwd=2)
```

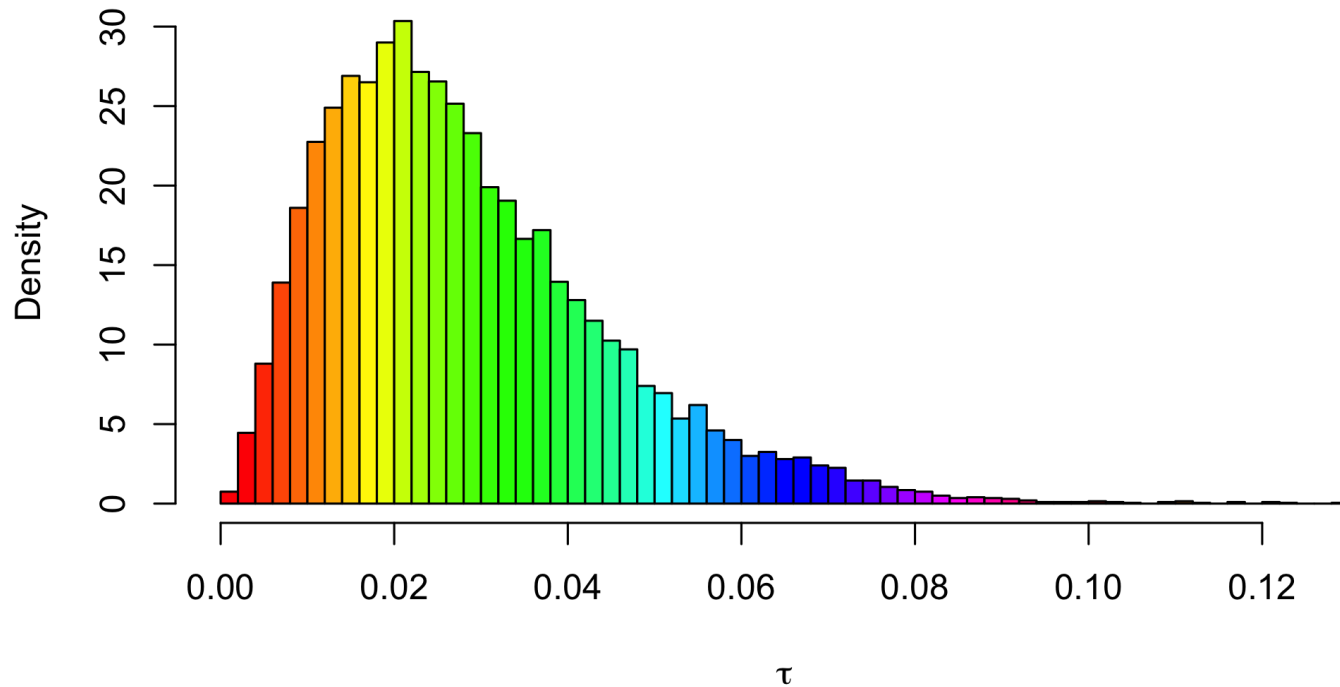
Sampled values of  $\tau$



# PYGMALION DATA: PRECISION

```
hist(PHI[,2],col=rainbow(50),xlab=expression(tau),ylab="Density",freq=F,breaks=50,  
main=expression(paste("Posterior density of ",tau)))
```

Posterior density of  $\tau$



# PYGMALION DATA: PRECISION

```
round(mean(PHI[,2]),3)
```

```
## [1] 0.028
```

```
round(quantile(PHI[,2],c(0.025,0.5,0.975)),3)
```

```
## 2.5% 50% 97.5%
```

```
## 0.006 0.025 0.069
```

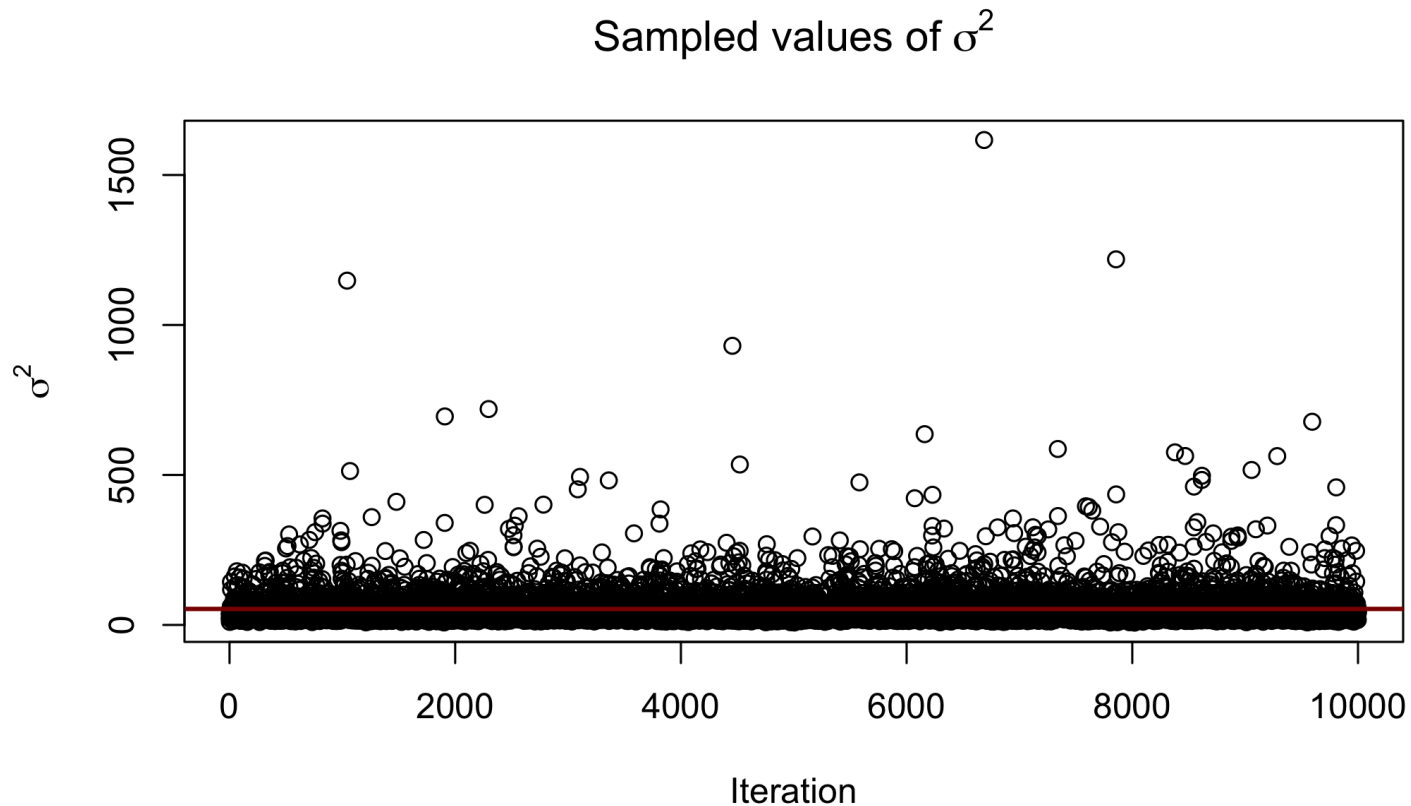
Posterior summaries for  $\tau$ :

- Posterior mean  $\approx 0.028$ .
- Posterior median  $\approx 0.025$ .
- 95% credible interval  $\approx (0.006, 0.069)$ .

For context,  $s_A = 4.71$ , which means sample precision =  $1/4.71^2 = 0.045$ .  
Also, we used a  $\text{Ga}(\frac{1}{2}, 50)$  prior for  $\tau$ .

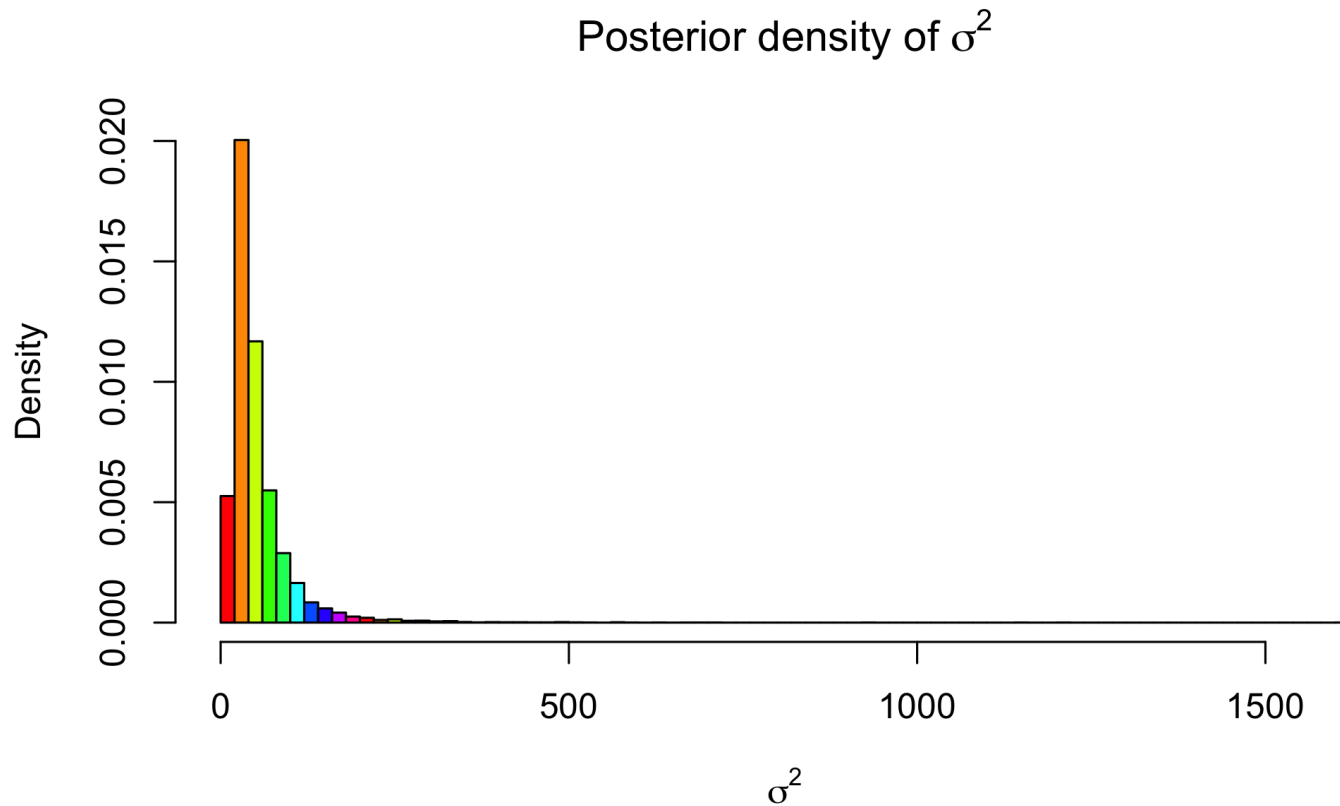
# PYGMALION DATA: VARIANCE

```
plot(PHI[,3],ylab=expression(sigma^2),xlab="Iteration",  
     main=expression(paste("Sampled values of ",sigma^2)))  
abline(a=mean(PHI[,3]),b=0,col="red4",lwd=2)
```



# PYGMALION DATA: VARIANCE

```
hist(PHI[,3],col=rainbow(10),xlab=expression(sigma^2),ylab="Density",freq=F,breaks=100,  
main=expression(paste("Posterior density of ",sigma^2)))
```





# PYGMALION DATA: VARIANCE

```
round(mean(PHI[,3]),2)
```

```
## [1] 53.34
```

```
round(quantile(PHI[,3],c(0.025,0.5,0.975)),2)
```

```
## 2.5% 50% 97.5%  
## 14.52 39.60 174.11
```

Posterior summaries for  $\sigma^2$ :

- Posterior mean = 53.34.
- Posterior median = 39.60.
- 95% credible interval = (14.52, 174.11).

For context,  $s_A = 4.71$ , which means sample variance  $4.71^2 = 22.18$ .  
Again, we used a  $\text{Ga}(\frac{1}{2}, 50)$  prior for  $\tau$ .

# WHAT'S NEXT?

MOVE ON TO THE READINGS FOR THE NEXT MODULE!