

# Homework 16

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```
rm(list = ls(all.names = TRUE)) #will clear all objects includes hidden objects.
gc() #free up memory and report the memory usage.
```

	used (Mb)	gc trigger (Mb)	limit (Mb)	max used (Mb)			
Ncells	569064	30.4	1291250	69	NA	669294	35.8
Vcells	1040814	8.0	8388608	64	32768	1839866	14.1

```
library(readr)
regression_example <- read_csv("regression_example.csv")
```

Rows: 1000 Columns: 2

-- Column specification -----

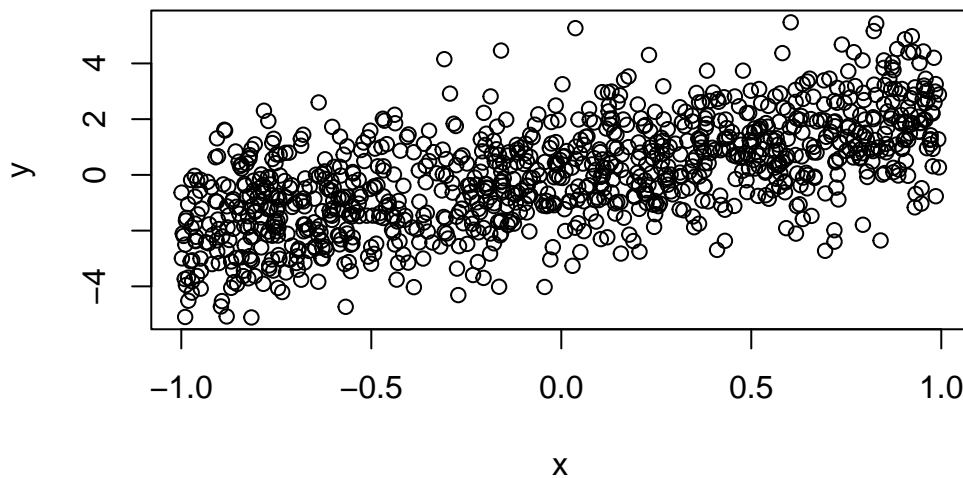
Delimiter: ","

dbl (2): x, y

i Use `spec()` to retrieve the full column specification for this data.

i Specify the column types or set `show\_col\_types = FALSE` to quiet this message.

```
x <- regression_example$x
y <- regression_example$y
plot(x,y)
```



```
lm <- lm(y~x-1,regression_example)
summary(lm)
```

Call:

```
lm(formula = y ~ x - 1, data = regression_example)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-4.1005	-0.9906	-0.0073	1.0555	5.1919

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
x	1.98469	0.07921	25.05	<2e-16 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.486 on 999 degrees of freedom

Multiple R-squared: 0.3859, Adjusted R-squared: 0.3853

F-statistic: 627.8 on 1 and 999 DF, p-value: < 2.2e-16

```
# Frequentist estimate of beta
beta_hat = sum((x - mean(x)) * (y - mean(y))) / sum((x - mean(x))^2)

# Frequentist estimate of sigma squared
sigma2_hat = sum((y - beta_hat * x)^2) / (length(y) - 1)
```

**i** [A] & [C] Using your expression from the previous part, proposals of the following form:

- $\beta \rightarrow \beta + \text{Unif}(-.2, .2)$
- $\sigma^2 \rightarrow \sigma^2 + \text{Unif}(-.1, .1)$

And the starting position  $\beta_0 = 2$ ,  $\sigma_0^2 = 2$ , first derive a Metropolis Hastings algorithm to approximate the posterior distribution  $\beta, \sigma^2 | Y_1, \dots, Y_n$ , and then write codes to simulate a Markov chain of length 10,000 using this algorithm. Use `set.seed(440)` in your simulations.

```
#initialize MH
beta0 = 2
sigma02 = 2

# Likelihood function on the log scale
likelihood = function(param){
  beta = param[1]
  var = param[2]
  pred = beta*x
  singlelikelihoods = dnorm(y, mean = pred, sd = sqrt(var), log = T)
  sumll = sum(singlelikelihoods)
  return(sumll)
}

# Prior distribution on the log scale
prior = function(param){
  beta = param[1]
  var = param[2]
  bprior = dnorm(beta, sd = sqrt(var), log = T)
  sdprior = log(1/var)
  return(bprior+sdprior)
}

# Posterior distribution on the log scale
posterior = function(param){
  return (likelihood(param) + prior(param))
}

proposalfunction = function(param){
  return(param + runif(2,c(-0.2,-0.1), c(0.2,0.1)))
}

run_metropolis_MCMC = function(startvalue, iterations){
  chain = array(dim = c(iterations+1,2))
  chain[1,] = startvalue
```

```

for (i in 1:iterations){
  proposal = proposalfunction(chain[i,])
  probab = exp(posterior(proposal) - posterior(chain[i,]))
  if (runif(1) < probab){
    chain[i+1,] = proposal
  }else{
    chain[i+1,] = chain[i,]
  }
}
return(chain)
}

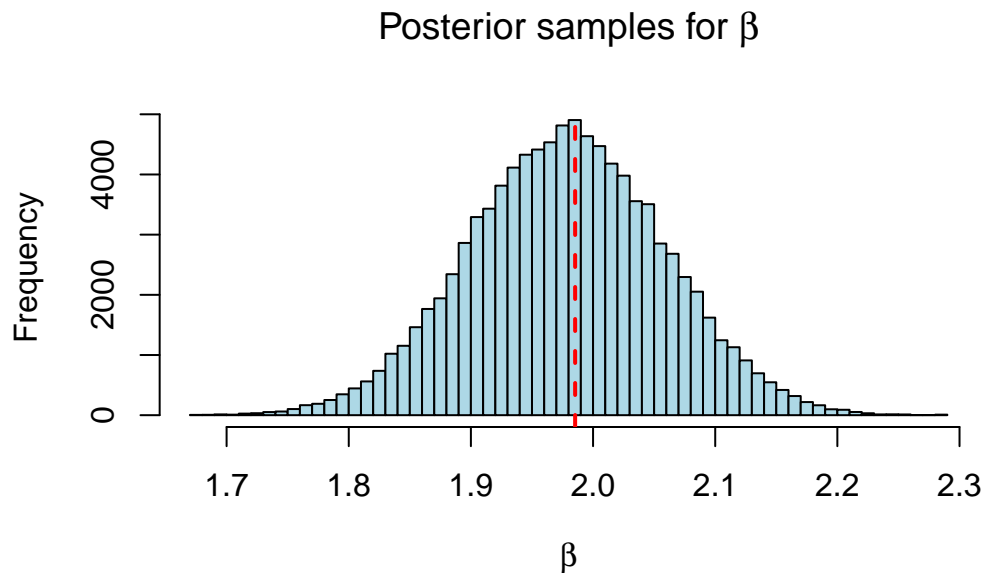
set.seed(440)
startvalue = c(beta0,sigma02)
chain = run_metropolis_MCMC(startvalue, 100000)

burnIn = 5000
beta_samples = chain[-(1:burnIn),1]
sigma_samples = chain[-(1:burnIn),2]

```

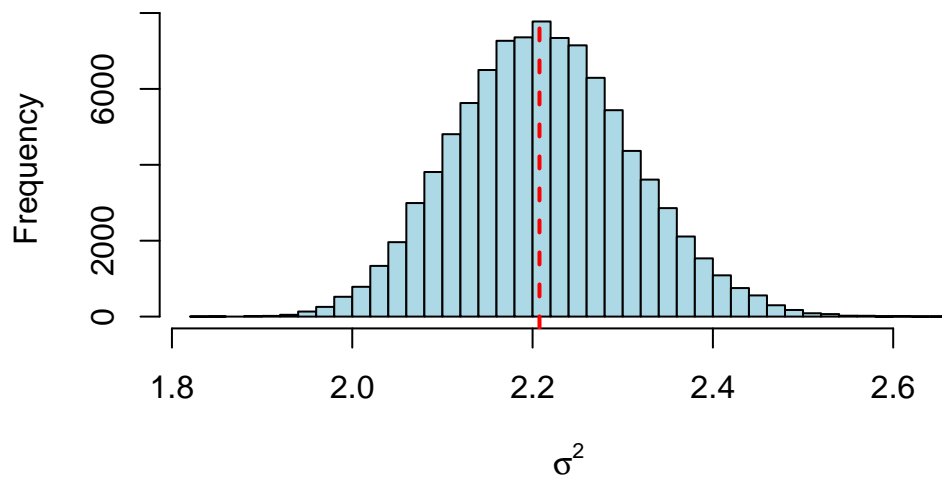
**i** [C] Plot the histograms of your simulated posterior samples for  $\beta$  and  $\sigma^2$  as two separate plots. Add a vertical line on each plot to indicate the frequentist estimates  $\hat{\beta}$  and  $\hat{\sigma}^2$

```
# Plot the histogram of beta with the frequentist estimate
hist(beta_samples,
      breaks = 50,
      main = expression("Posterior samples for " * beta),
      xlab = expression(beta),
      col = "lightblue",
      border = "black")
abline(v = beta_hat, col = "red", lwd = 2, lty = 2)
```



```
# Plot the histogram of sigma^2 with the frequentist estimate
hist(sigma_samples,
      breaks = 50,
      main = expression("Posterior samples for " * sigma^2),
      xlab = expression(sigma^2),
      col = "lightblue",
      border = "black")
abline(v = sigma2_hat, col = "red", lwd = 2, lty = 2)
```

Posterior samples for  $\sigma^2$



**i** [C] Using your simulated posterior samples, calculate a 95% credible interval for  $\beta$

```
# Calculate the 95% posterior credible interval for b
ci_95 <- quantile(beta_samples, probs = c(0.025, 0.975))
ci_95

      2.5%      97.5%
1.821517 2.134177

hist(beta_samples,
      breaks = 50,
      main = expression("95% posterior credible interval for " * beta),
      xlab = expression(beta),
      col = "lightblue",
      border = "black")
abline(v = ci_95, col = "red", lwd = 2, lty = 2)
```

