

Homework 09 - STAT440

Joseph Sepich (jps6444)

11/08/2020

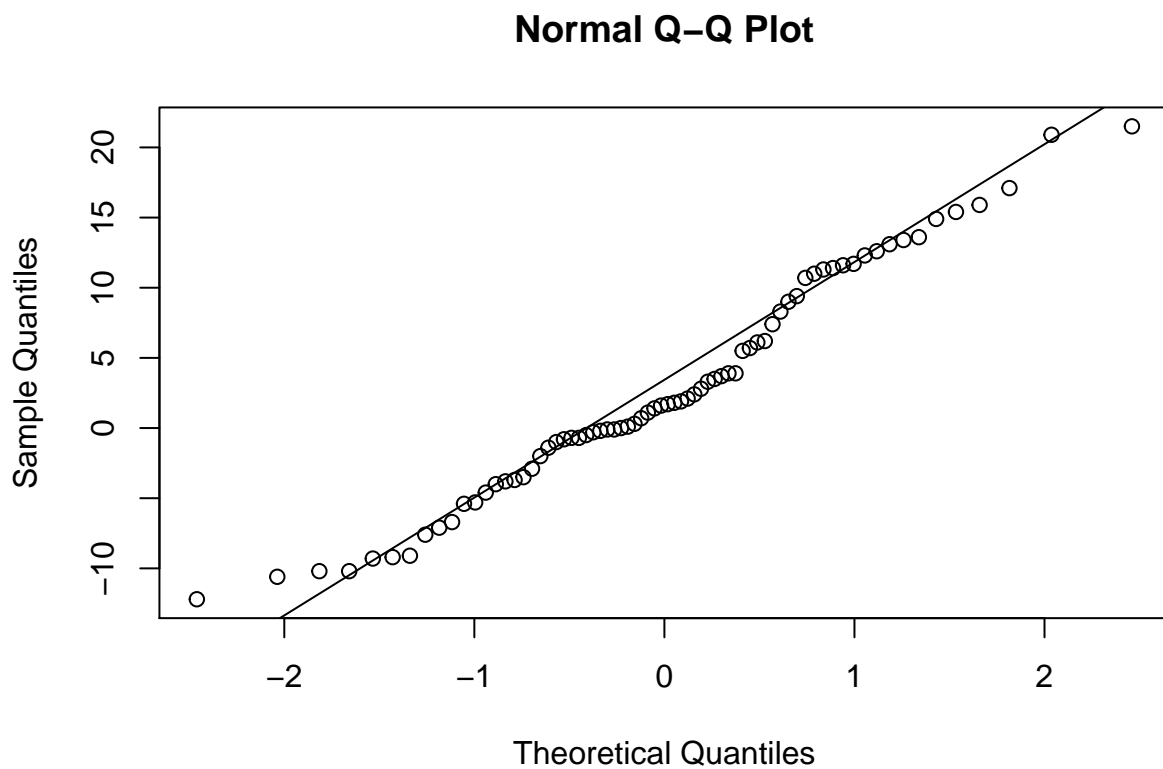
```
set.seed(42)
```

Problem 1

```
df$Weight_Increase <- df$Postwt - df$Prewt
```

Part a

```
qqnorm(df$Weight_Increase)  
qqline(df$Weight_Increase)
```

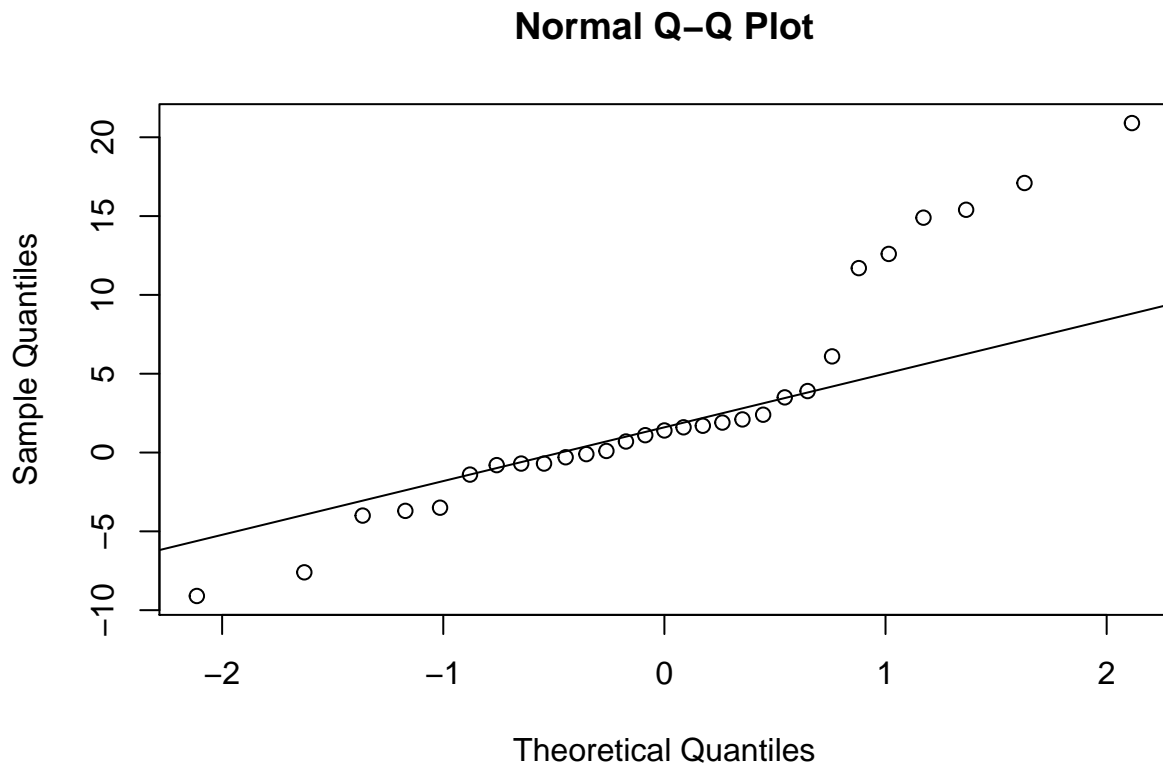


```
#qqplot(y, rt(300, df = 5))
```

The results follow the diagonal line (theoretical quantile match) fairly closely, but the tail to the left is steeper than the tail on the right compared to the normal, since the data points lie under the normal line of quantiles.

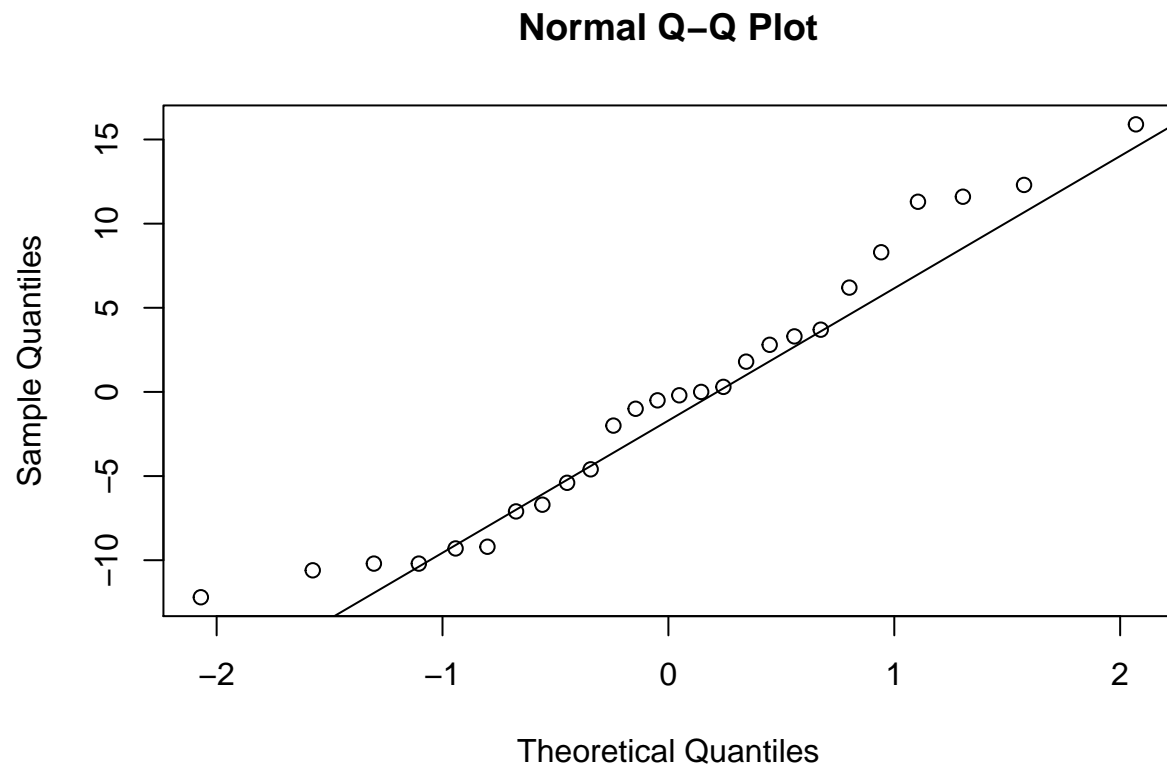
Part b

```
# CBT
df %>%
  filter(Treat == 'CBT') %>%
  .$Weight_Increase %>%
  qqnorm()
df %>%
  filter(Treat == 'CBT') %>%
  .$Weight_Increase %>%
  qqline()
```

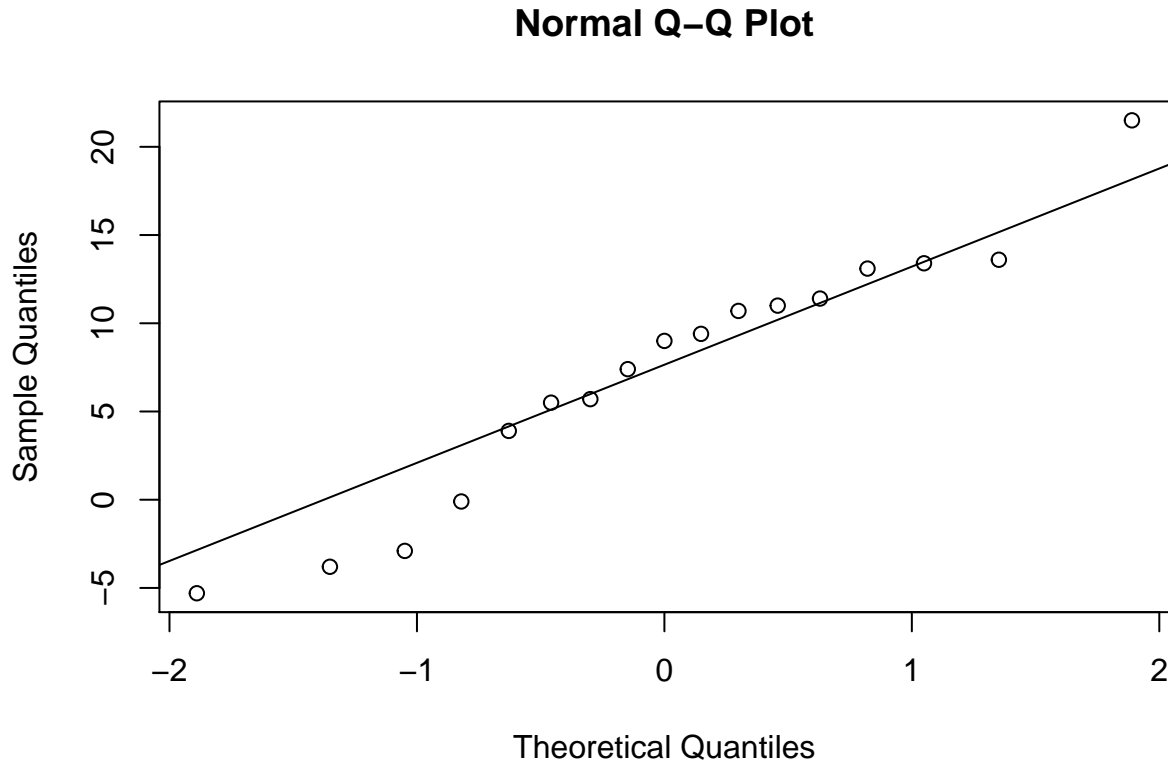


```
# Cont
df %>%
  filter(Treat == 'Cont') %>%
  .$Weight_Increase %>%
  qqnorm()
```

```
df %>%
  filter(Treat == 'Cont') %>%
  .$Weight_Increase %>%
  qqline()
```



```
# FT
df %>%
  filter(Treat == 'FT') %>%
  .$Weight_Increase %>%
  qqnorm()
df %>%
  filter(Treat == 'FT') %>%
  .$Weight_Increase %>%
  qqline()
```



Each of the three groups roughly follow a gaussian distribution. Actually a lot of the middle quantiles match up for the CBT group, which is promising and this trend of having the middle quantiles match up also happens with the other two treatment groups, so we likely can approximate the distribution using a gaussian distribution.

Problem 2

Part a

The conjugate prior to the likelihood for the normal distribution is the normal distribution. Our posterior is then also a normal distribution.

Part b

The mean of the prior is essentially our initial assumption about where the mean is for the true distribution. I will therefore set the prior parameter $\mu_0 = 0$ which would operate under the assumption that the average weight increase after treatment is zero. This would essentially say we expect there to be no weight increase after treatment. Using this as our prior parameter can help us to see how much our evidence shows of an actual weight increase by looking at the posterior parameter we receive from the evidence. (We do not need to decide on a prior variance since we are operating on the assumption that our sample variance is the fixed know variance.)

Part c

$$\sigma_0^2 \rightarrow \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2}\right)^{-1}$$

$$\mu_0 \rightarrow \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2}\right)^{-1} \left(\frac{n\bar{X}}{\sigma^2} + \frac{\mu_0}{\sigma_0^2}\right)$$

```
update_sigma <- function(x, prior_sig, sig=1) {
  (length(x) / sig^2 + 1 / prior_sig^2) ^ -1
}

update_mu <- function(x, prior_mu, prior_sig, sig=1) {
  update_sigma(prior_sig, sig) * (length(x) * mean(x) / sig^2 + prior_mu / prior_sig^2)
}
```

```
df_cbt <- df %>%
  filter(Treat == 'CBT')
df_cont <- df %>%
  filter(Treat == 'Cont')
df_ft <- df %>%
  filter(Treat == 'FT')

prior_sigma_cbt <- sd(df_cbt$Weight_Increase)
prior_mu_cbt <- 0
prior_sigma_cont <- sd(df_cont$Weight_Increase)
prior_mu_cont <- 0
prior_sigma_ft <- sd(df_ft$Weight_Increase)
prior_mu_ft <- 0
```

```
print(paste0('Prior CBT: ', prior_sigma_cbt, ' ', prior_mu_cbt))
```

```
## [1] "Prior CBT: 7.30850439236387 0"
```

```
print(paste0('Prior Cont: ', prior_sigma_cont, ' ', prior_mu_cont))
```

```
## [1] "Prior Cont: 7.98870452576637 0"
```

```
print(paste0('Prior FT: ', prior_sigma_ft, ' ', prior_mu_ft))
```

```
## [1] "Prior FT: 7.15742107679772 0"
```

```
post_sigma_cbt <- update_sigma(df_cbt$Weight_Increase, prior_sigma_cbt, prior_sigma_cbt)
post_mu_cbt <- update_mu(df_cbt$Weight_Increase, prior_mu_cbt, prior_sigma_cbt, prior_sigma_cbt)
post_sigma_cont <- update_sigma(df_cont$Weight_Increase, prior_sigma_cont, prior_sigma_cont)
post_mu_cont <- update_mu(df_cont$Weight_Increase, prior_mu_cont, prior_sigma_cont, prior_sigma_cont)
post_sigma_ft <- update_sigma(df_ft$Weight_Increase, prior_sigma_ft, prior_sigma_ft)
post_mu_ft <- update_mu(df_ft$Weight_Increase, prior_mu_ft, prior_sigma_ft, prior_sigma_ft)
```

```
print(paste0('Posterior CBT: ', post_sigma_cbt, ' ', post_mu_cbt))
```

```
## [1] "Posterior CBT: 1.78047454844007 1.60252179730565"
```

```
print(paste0('Posterior Cont: ', post_sigma_cont, ' ', post_mu_cont))
```

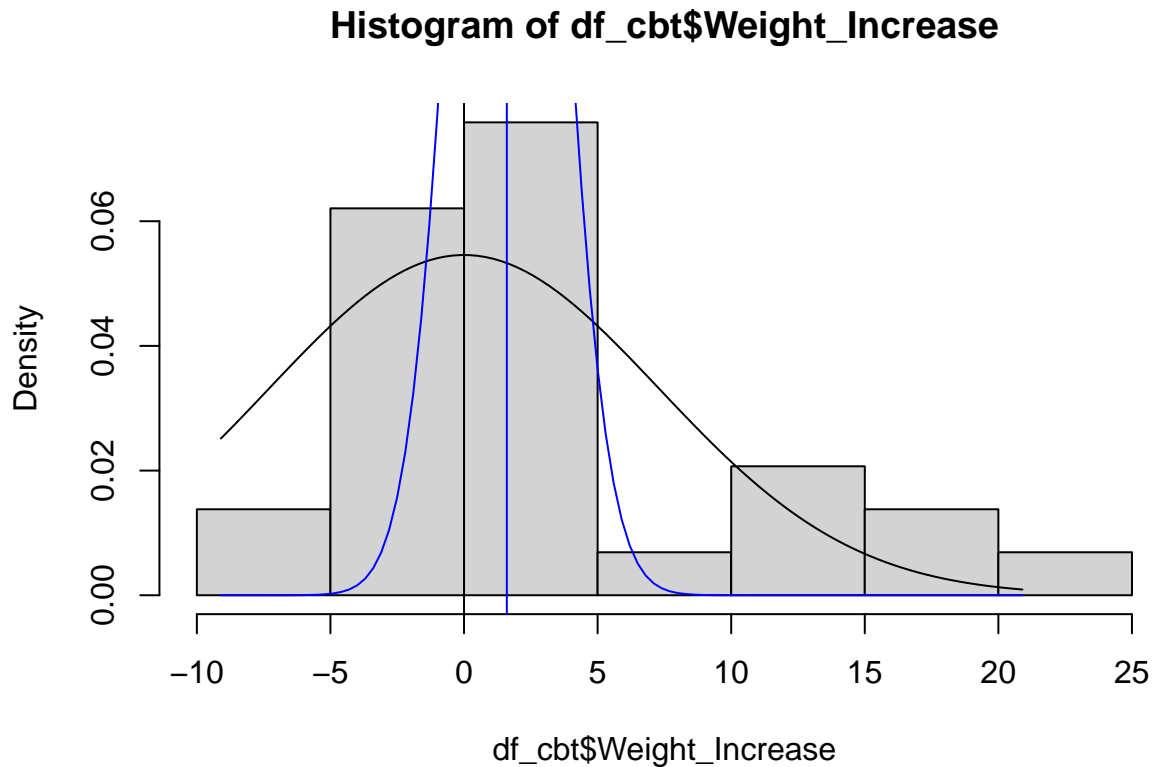
```
## [1] "Posterior Cont: 2.36368148148148 -0.180501516521288"
```

```
print(paste0('Posterior FT: ', post_sigma_ft, ' ', post_mu_ft))
```

```
## [1] "Posterior FT: 2.84603758169935 2.36460137123228"
```

Part d

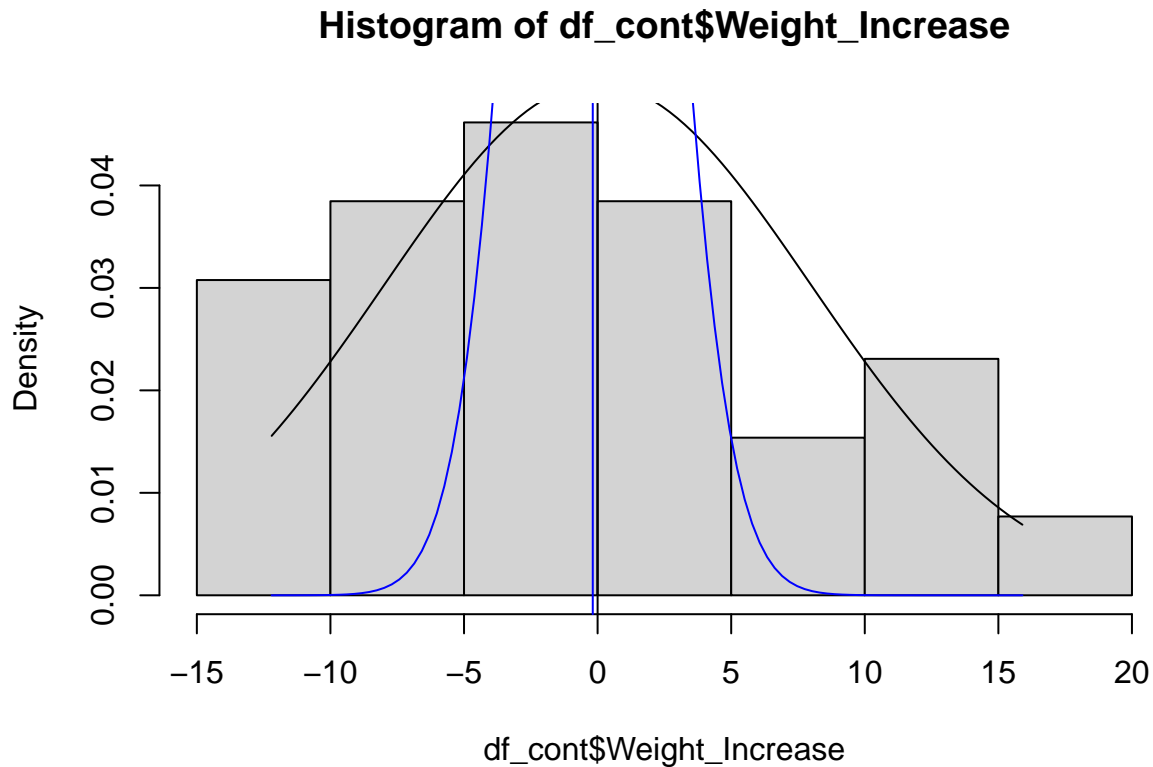
```
min_x <- min(df_cbt$Weight_Increase)
max_x <- max(df_cbt$Weight_Increase)
hist(df_cbt$Weight_Increase, freq=F)
curve(dnorm(x,mean=prior_mu_cbt,sd=prior_sigma_cbt), min_x, max_x, add=T, col='black')
abline(v=prior_mu_cbt,col='black')
curve(dnorm(x,mean=post_mu_cbt,sd=post_sigma_cbt), min_x, max_x, add=T, col='blue')
abline(v=post_mu_cbt,col='blue')
```



```

min_x <- min(df_cont$Weight_Increase)
max_x <- max(df_cont$Weight_Increase)
hist(df_cont$Weight_Increase, freq=F)
curve(dnorm(x,mean=prior_mu_cont,sd=prior_sigma_cont), min_x, max_x, add=T, col='black')
abline(v=prior_mu_cont,col='black')
curve(dnorm(x,mean=post_mu_cont,sd=post_sigma_cont), min_x, max_x, add=T, col='blue')
abline(v=post_mu_cont,col='blue')

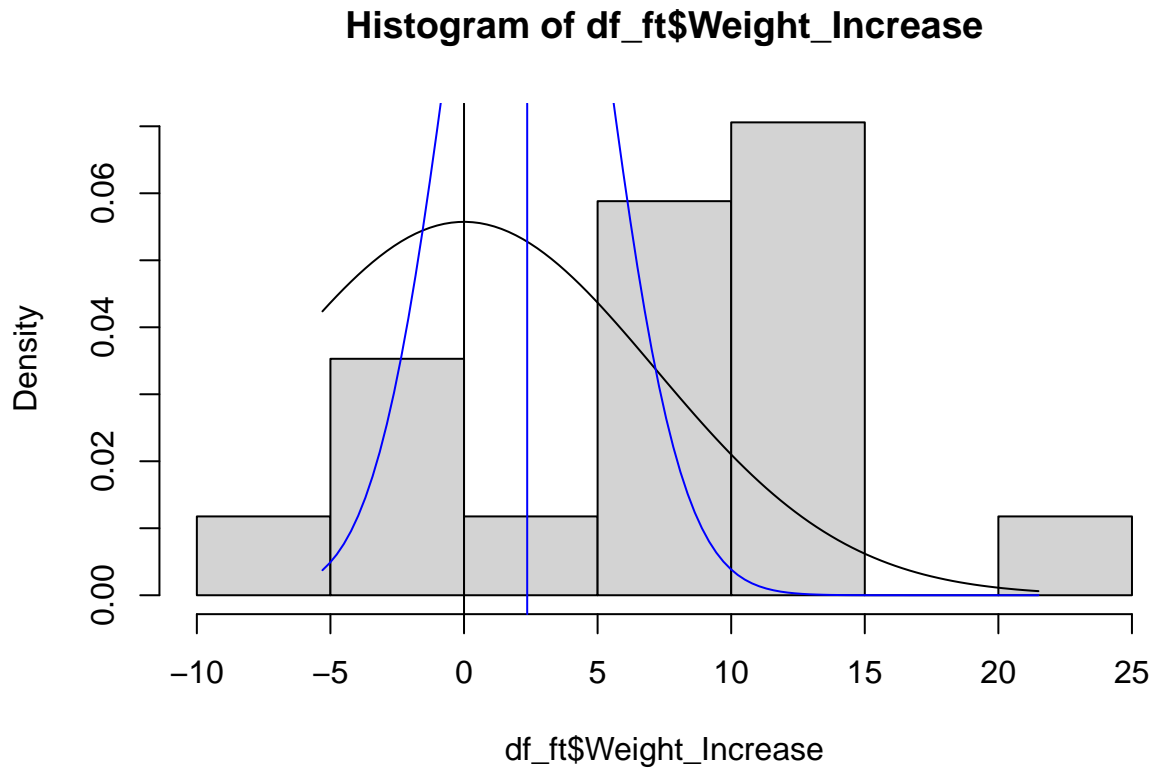
```



```

min_x <- min(df_ft$Weight_Increase)
max_x <- max(df_ft$Weight_Increase)
hist(df_ft$Weight_Increase, freq=F)
curve(dnorm(x,mean=prior_mu_ft,sd=prior_sigma_ft), min_x, max_x, add=T, col='black')
abline(v=prior_mu_ft,col='black')
curve(dnorm(x,mean=post_mu_ft,sd=post_sigma_ft), min_x, max_x, add=T, col='blue')
abline(v=post_mu_ft,col='blue')

```



The above charts have the actual data plotted a histogram, the black curve is the prior distribution, and the posterior distribution is the blue curve. We can see that in each of the three plots the posterior mean moved from zero toward the mean of the data points, or evidence, we have in our data set. It is also important to note that the variance of the posterior distribution also decreased for each plot. This decrease indicates more confidence in our posterior estimate of μ , since the posterior has more evidence behind it than the prior. Along the same line of thinking the group with the most data point had the smallest posterior variance.

Part e

```
M <- 1000
c_val <- 0.05

samples_cbt <- rnorm(M, post_mu_cbt, post_sigma_cbt)
samples_cont <- rnorm(M, post_mu_cont, post_sigma_cont)
samples_ft <- rnorm(M, post_mu_ft, post_sigma_ft)

prob_vec <- c(c_val, 1-c_val)
ci_cbt <- quantile(samples_cbt, probs=prob_vec)
ci_cont <- quantile(samples_cont, probs=prob_vec)
ci_ft <- quantile(samples_ft, probs=prob_vec)

print(paste0('CBT Cred Int: ', ci_cbt))

## [1] "CBT Cred Int: -1.32704024556603" "CBT Cred Int: 4.33285652875773"
```



```
print(paste0('Cont Cred Int: ', ci_cont))
```

```
## [1] "Cont Cred Int: -4.06134687688708" "Cont Cred Int: 3.64911468805187"
```

```
print(paste0('FT Cred Int: ', ci_ft))
```

```
## [1] "FT Cred Int: -2.68692425774453" "FT Cred Int: 7.14890869430698"
```

According to this analysis our evidence is not credible enough to determine that any of the treatments had an effect that raised (or lowered) weight in the anorexic patients.

Problem 3

Part a

The conjugate prior to the likelihood for the normal distribution is the inverse gamma distribution. Our posterior is then also an inverse gamma distribution.

Part b

For the inverse gamma distribution I will use the prior parameters $\alpha = \beta = 1$. The inverse gamma distribution for these parameters is flatter and has a rather thick tail. This flatter density is more desirable for our prior, since we are basically stating we are unsure where exactly the variance is by having a rather flat pdf. The inverse gamma also does not have a defined mean for this value of α , since the tail is too thick. This makes our prior “knowledge” have no claim about an exact starting variance value.

Part c

$$\alpha \rightarrow \alpha + n/2$$
$$\beta \rightarrow \beta + \frac{1}{2} \sum (X_i - \mu)^2$$

```
update_alpha <- function(x, prior_alpha) {  
  prior_alpha + length(x) / 2  
}  
  
update_beta <- function(x, prior_beta, mu) {  
  prior_beta + 0.5 * (sum((x - mu)^2))  
}
```

```
df_cbt <- df %>%  
  filter(Treat == 'CBT')  
df_cont <- df %>%  
  filter(Treat == 'Cont')  
df_ft <- df %>%  
  filter(Treat == 'FT')  
  
true_sig_cbt <- sd(df_cbt$Weight_Increase)
```

```
true_sig_cont <- sd(df_cbt$Weight_Increase)
true_sig_ft <- sd(df_cbt$Weight_Increase)
```

```
prior_alpha_cbt <- 1
prior_beta_cbt <- 1
prior_alpha_cont <- 1
prior_beta_cont <- 1
prior_alpha_ft <- 1
prior_beta_ft <- 1
```

```
print(paste0('Prior CBT: ', prior_alpha_cbt, ' ', prior_beta_cbt))
```

```
## [1] "Prior CBT: 1 1"
```

```
print(paste0('Prior Cont: ', prior_alpha_cont, ' ', prior_beta_cont))
```

```
## [1] "Prior Cont: 1 1"
```

```
print(paste0('Prior FT: ', prior_alpha_ft, ' ', prior_beta_ft))
```

```
## [1] "Prior FT: 1 1"
```

```
post_alpha_cbt <- update_alpha(df_cbt$Weight_Increase, prior_alpha_cbt)
post_beta_cbt <- update_beta(df_cbt$Weight_Increase, prior_beta_cbt, mean(df_cbt$Weight_Increase))
post_alpha_cont <- update_alpha(df_cont$Weight_Increase, prior_alpha_cont)
post_beta_cont <- update_beta(df_cont$Weight_Increase, prior_beta_cont, mean(df_cont$Weight_Increase))
post_alpha_ft <- update_alpha(df_ft$Weight_Increase, prior_alpha_ft)
post_beta_ft <- update_beta(df_ft$Weight_Increase, prior_beta_ft, mean(df_ft$Weight_Increase))
```

```
print(paste0('Posterior CBT: ', post_alpha_cbt, ' ', post_beta_cbt))
```

```
## [1] "Posterior CBT: 15.5 748.799310344828"
```

```
print(paste0('Posterior Cont: ', post_alpha_cont, ' ', post_beta_cont))
```

```
## [1] "Posterior Cont: 14 798.7425"
```

```
print(paste0('Posterior FT: ', post_alpha_ft, ' ', post_beta_ft))
```

```
## [1] "Posterior FT: 9.5 410.829411764706"
```

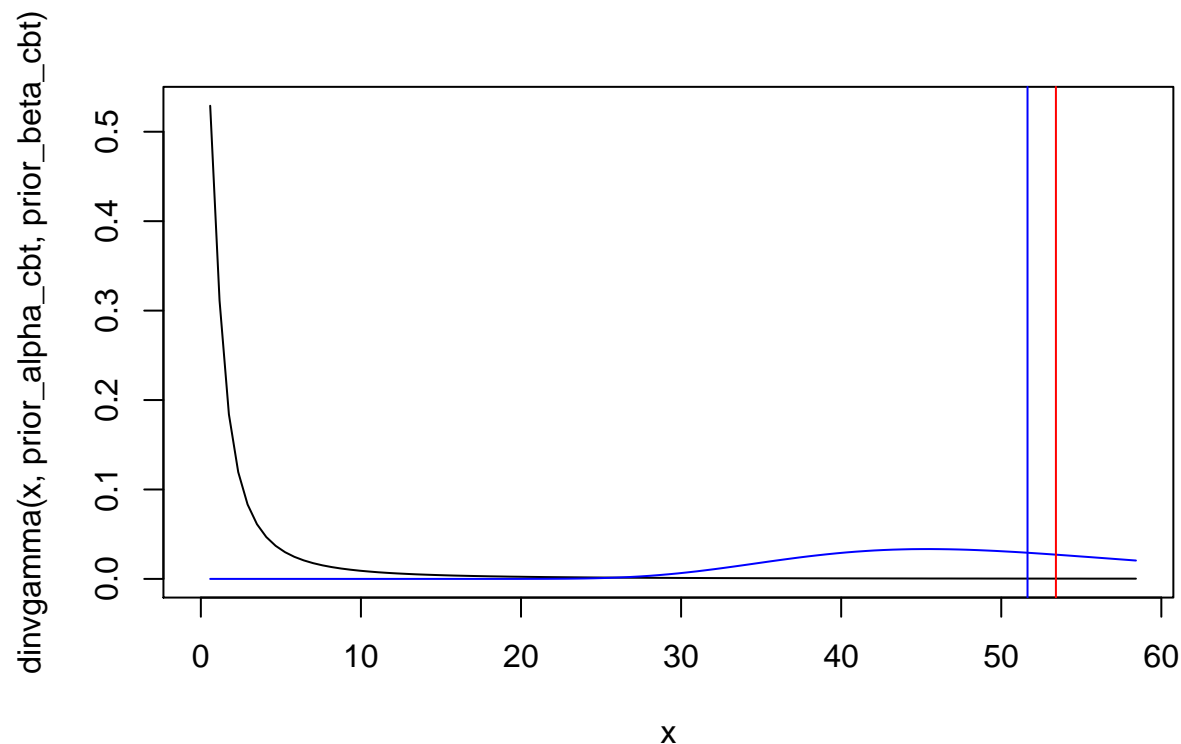
Part d

```
library(invgamma)
```

```

curve(dinvgamma(x,prior_alpha_cbt,prior_beta_cbt), 0, true_sig_cbt^2 + 5, col='black')
curve(dinvgamma(x,post_alpha_cbt,post_beta_cbt), 0, true_sig_cbt^2 + 5, add=T, col='blue')
abline(v=post_beta_cbt/(post_alpha_cbt-1),col='blue')
abline(v=true_sig_cbt^2,col='red')

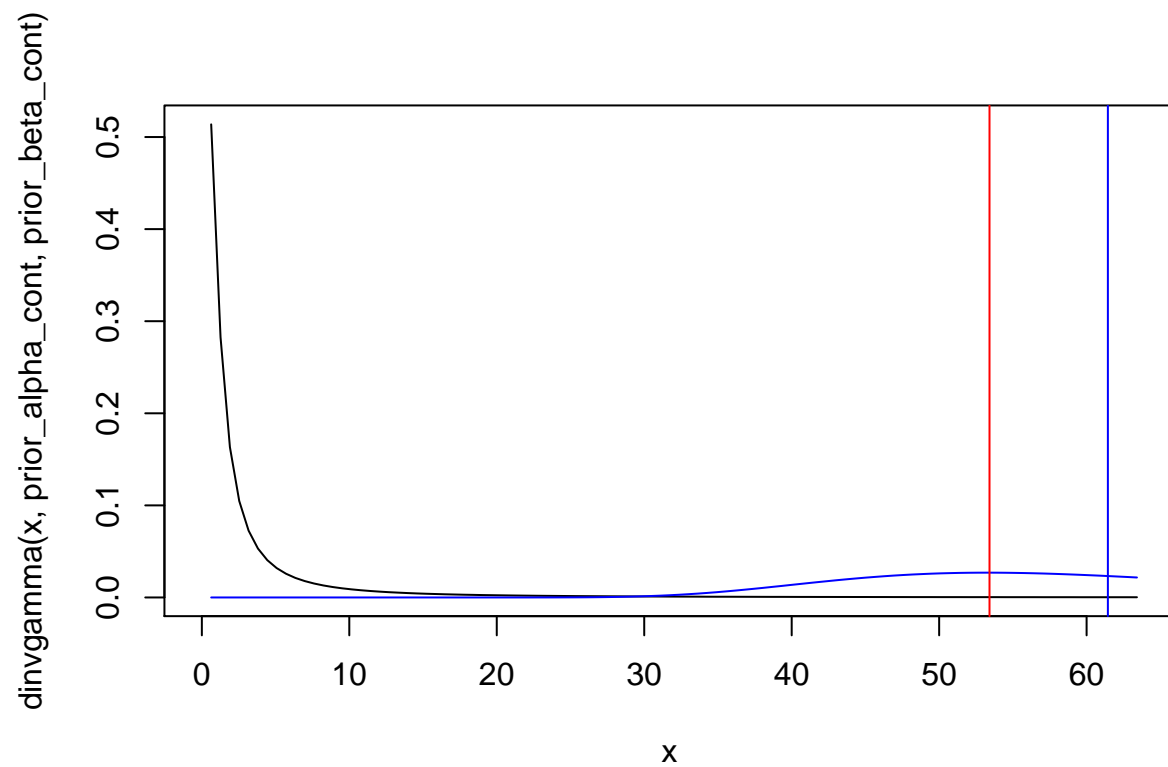
```



```

curve(dinvgamma(x,prior_alpha_cont,prior_beta_cont), 0, true_sig_cont^2 + 10, col='black')
curve(dinvgamma(x,post_alpha_cont,post_beta_cont), 0, true_sig_cont^2 + 10, add=T, col='blue')
abline(v=post_beta_cont/(post_alpha_cont-1),col='blue')
abline(v=true_sig_cont^2,col='red')

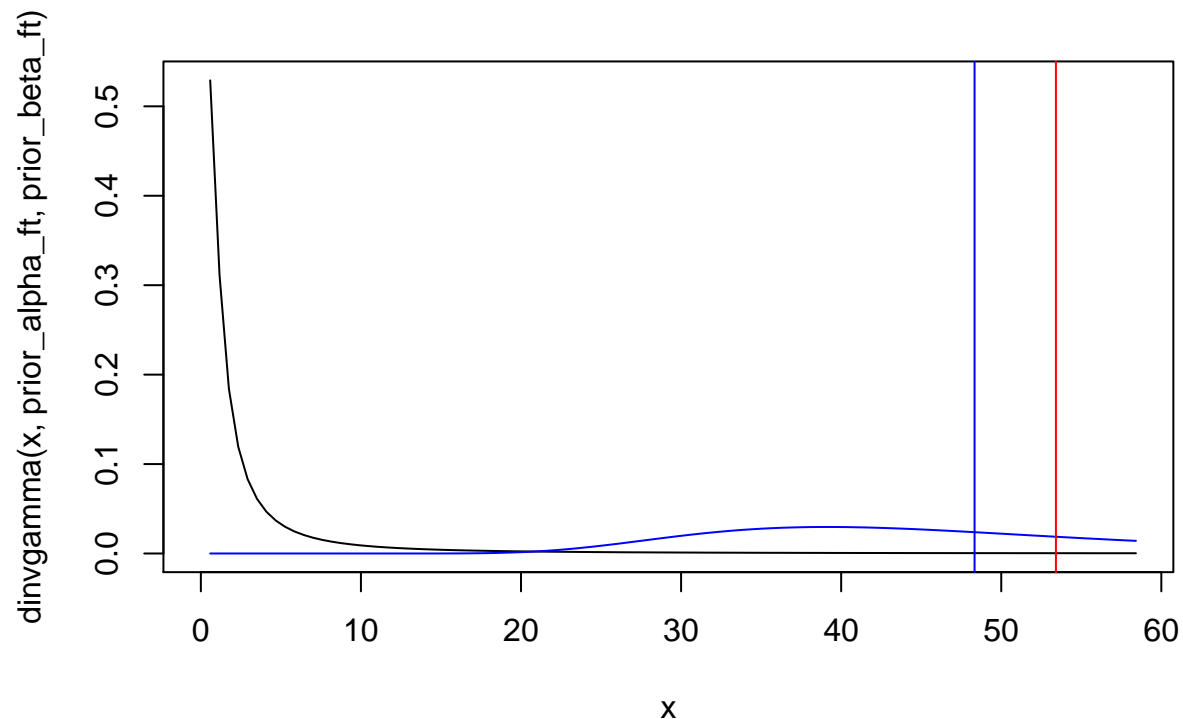
```



```

curve(dlnGamma(x,prior_alpha_ft,prior_beta_ft), 0, true_sig_ft^2 + 5, col='black')
curve(dlnGamma(x,post_alpha_ft,post_beta_ft), 0, true_sig_ft^2 + 5, add=T, col='blue')
abline(v=post_beta_ft/(post_alpha_ft-1),col='blue')
abline(v=true_sig_ft^2,col='red')

```



The above charts have two curves. The black curve is the prior distribution, and the posterior distribution is the blue curve. In each of the three plots the inverse gamma function moves into a much flatter shape centered around a much higher variance. The vertical blue line denotes the mean of the inverse gamma function and the red line denotes the variance found in our data. In each of the three cases we can see that the change in the distribution followed from the variance of our data. Each group had the inverse gamma move to be close to the sample variance of the data.

Part e

```
M <- 1000
c_val <- 0.05

samples_cbt <- rinvgamma(M, post_alpha_cbt, post_beta_cbt)
samples_cont <- rinvgamma(M, post_alpha_cont, post_beta_cont)
samples_ft <- rinvgamma(M, post_alpha_ft, post_beta_ft)

prob_vec <- c(c_val, 1-c_val)
ci_cbt <- quantile(samples_cbt, probs=prob_vec)
ci_cont <- quantile(samples_cont, probs=prob_vec)
ci_ft <- quantile(samples_ft, probs=prob_vec)

print(paste0('CBT Cred Int: ', ci_cbt))

## [1] "CBT Cred Int: 33.1609994532744" "CBT Cred Int: 81.6334516464406"
```

```
print(paste0('Cont Cred Int: ', ci_cont))
```

```
## [1] "Cont Cred Int: 39.1235443488929" "Cont Cred Int: 93.081136934695"
```

```
print(paste0('FT Cred Int: ', ci_ft))
```

```
## [1] "FT Cred Int: 26.8359911134677" "FT Cred Int: 78.3138089294551"
```

According to this analysis our evidence is credible enough to determine that any of the variance of the distribution around our sample mean is between 25 and 95 for all of the groups. The FT treatment had the lowest variance values and the control treatment group had the highest variance values. Perhaps this could indicate that the treatment groups actually had some effect, since they did not vary as much as the “untouched” control group.

Problem 4

Part a

For the full normal setting we essentially use the same prior and posterior equations as before, but we set the conjugate prior/posterior for the mean to be dependent on the variance belief set. For example:

$$\pi(\sigma^2) \text{ InvGamma}(\alpha, \beta)$$

$$\pi(\mu|\sigma^2) N(\mu_0, \sigma^2/n_0)$$

Part b

We will use the same prior parameters as before for the same reasoning where $\mu = 0, \alpha = \beta = 1$. We do have an introduction of a new parameter n_0 . This parameter affects the variance of the normal distribution that states our beliefs about the sample mean. We will initialize this to 1. n_0 is basically a representation of the number of samples we have collected so far, but we cannot divide by zero, so we will start at 1.

Part c

$$\alpha \rightarrow \alpha + n/2$$

$$\beta \rightarrow \beta + \frac{1}{2} \sum (X_i - \bar{X})^2 + \frac{n_0 n}{2(n + n_0)} (\bar{X} - \mu_0)^2$$

$$\sigma_0^2 \rightarrow \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2} \right)^{-1}$$

$$\mu_0 \rightarrow \frac{n}{n + n_0} \bar{X} + \frac{n_0}{n + n_0} \mu_0$$

$$n_0 \rightarrow n_0 + n$$

```

update_alpha <- function(x, prior_a) {
  prior_a + length(x) / 2
}

update_beta <- function(x, prior_b, prior_mu, prior_n) {
  x_bar <- mean(x)
  n <- length(x)

  result <- prior_b
  result <- result + 0.5 * sum((x - x_bar)^2)
  result <- result + (n * prior_n) / (2 * (n + prior_n)) * (x_bar - prior_mu)^2
  result
}

update_mu <- function(x, prior_mu, prior_n) {
  x_bar <- mean(x)
  n <- length(x)

  result <- n / (n + prior_n) * x_bar
  result <- result + prior_n / (n + prior_n) * prior_mu
  result
}

update_n <- function(x, prior_n) {
  length(x) + prior_n
}

```

```

p_a_cbt <- 1
p_b_cbt <- 1
p_mu_cbt <- 0
p_n_cbt <- 1
p_a_cont <- 1
p_b_cont <- 1
p_mu_cont <- 0
p_n_cont <- 1
p_a_ft <- 1
p_b_ft <- 1
p_mu_ft <- 0
p_n_ft <- 1

```

```
print(paste0('Prior Params Alpha, Beta, Mu, N'))
```

```
## [1] "Prior Params Alpha, Beta, Mu, N"
```

```
print(paste0('Prior CBT: ', p_a_cbt, ', ', p_b_cbt, ', ', p_mu_cbt, ', ', p_n_cbt))
```

```
## [1] "Prior CBT: 1, 1, 0, 1"
```

```
print(paste0('Prior CBT: ', p_a_cont, ', ', p_b_cont, ', ', p_mu_cont, ', ', p_n_cont))
```

```
## [1] "Prior CBT: 1, 1, 0, 1"
```

```
print(paste0('Prior CBT: ', p_a_ft, ', ', p_b_ft, ', ', p_mu_ft, ', ', p_n_ft))
```

```
## [1] "Prior CBT: 1, 1, 0, 1"
```

```
po_a_cbt <- update_alpha(df_cbt$Weight_Increase, p_a_cbt)
po_b_cbt <- update_beta(df_cbt$Weight_Increase, p_b_cbt, p_mu_cbt, p_n_cbt)
po_mu_cbt <- update_mu(df_cbt$Weight_Increase, p_mu_cbt, p_n_cbt)
po_n_cbt <- update_n(df_cbt$Weight_Increase, p_n_cbt)
po_a_cont <- update_alpha(df_cont$Weight_Increase, p_a_cont)
po_b_cont <- update_beta(df_cont$Weight_Increase, p_b_cont, p_mu_cont, p_n_cont)
po_mu_cont <- update_mu(df_cont$Weight_Increase, p_mu_cont, p_n_cont)
po_n_cont <- update_n(df_cont$Weight_Increase, p_n_cont)
po_a_ft <- update_alpha(df_ft$Weight_Increase, p_a_ft)
po_b_ft <- update_beta(df_ft$Weight_Increase, p_b_ft, p_mu_ft, p_n_ft)
po_mu_ft <- update_mu(df_ft$Weight_Increase, p_mu_ft, p_n_ft)
po_n_ft <- update_n(df_ft$Weight_Increase, p_n_ft)
```

```
print(paste0('Posterior Params Alpha, Beta, Mu, N'))
```

```
## [1] "Posterior Params Alpha, Beta, Mu, N"
```

```
print(paste0('Posterior CBT: ', po_a_cbt, ', ', po_b_cbt, ', ', po_mu_cbt, ', ', po_n_cbt))
```

```
## [1] "Posterior CBT: 15.5, 753.169333333334, 2.90666666666667, 30"
```

```
print(paste0('Posterior CBT: ', po_a_cont, ', ', po_b_cont, ', ', po_mu_cont, ', ', po_n_cont))
```

```
## [1] "Posterior CBT: 14, 798.84, -0.433333333333332, 27"
```

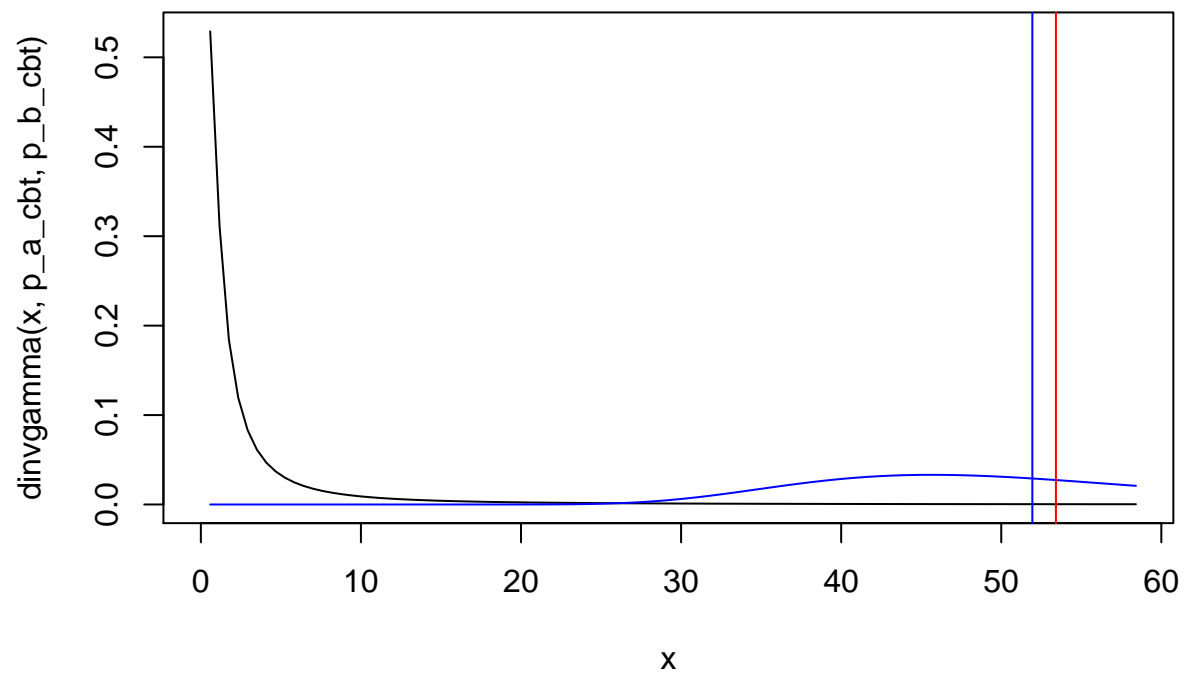
```
print(paste0('Posterior CBT: ', po_a_ft, ', ', po_b_ft, ', ', po_mu_ft, ', ', po_n_ft))
```

```
## [1] "Posterior CBT: 9.5, 435.751388888889, 6.86111111111111, 18"
```

Part d

First we plot the variance distributions.

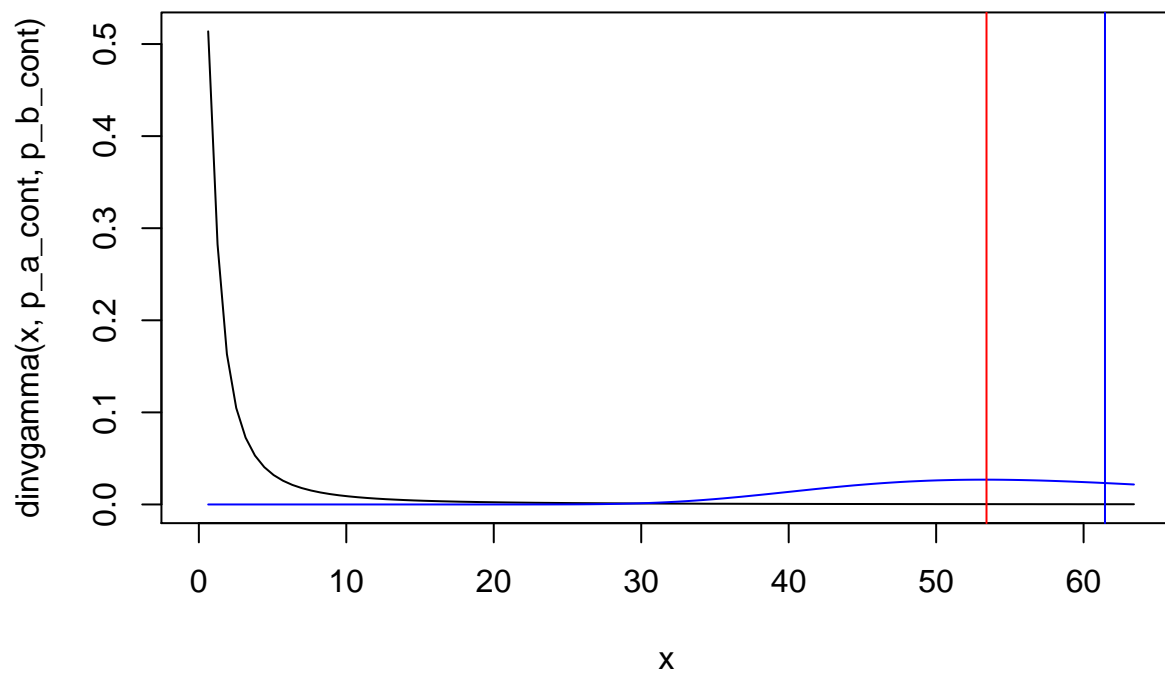
```
curve(dinvgamma(x,p_a_cbt,p_b_cbt), 0, true_sig_cbt^2 + 5, col='black')
curve(dinvgamma(x,po_a_cbt,po_b_cbt), 0, true_sig_cbt^2 + 5, add=T, col='blue')
abline(v=po_b_cbt/(po_a_cbt-1),col='blue')
abline(v=true_sig_cbt^2,col='red')
```

```

curve(dinvgamma(x,p_a_cont,p_b_cont), 0, true_sig_cont^2 + 10, col='black')
curve(dinvgamma(x,po_a_cont,po_b_cont), 0, true_sig_cont^2 + 10, add=T, col='blue')
abline(v=po_b_cont/(po_a_cont-1),col='blue')
abline(v=true_sig_cont^2,col='red')

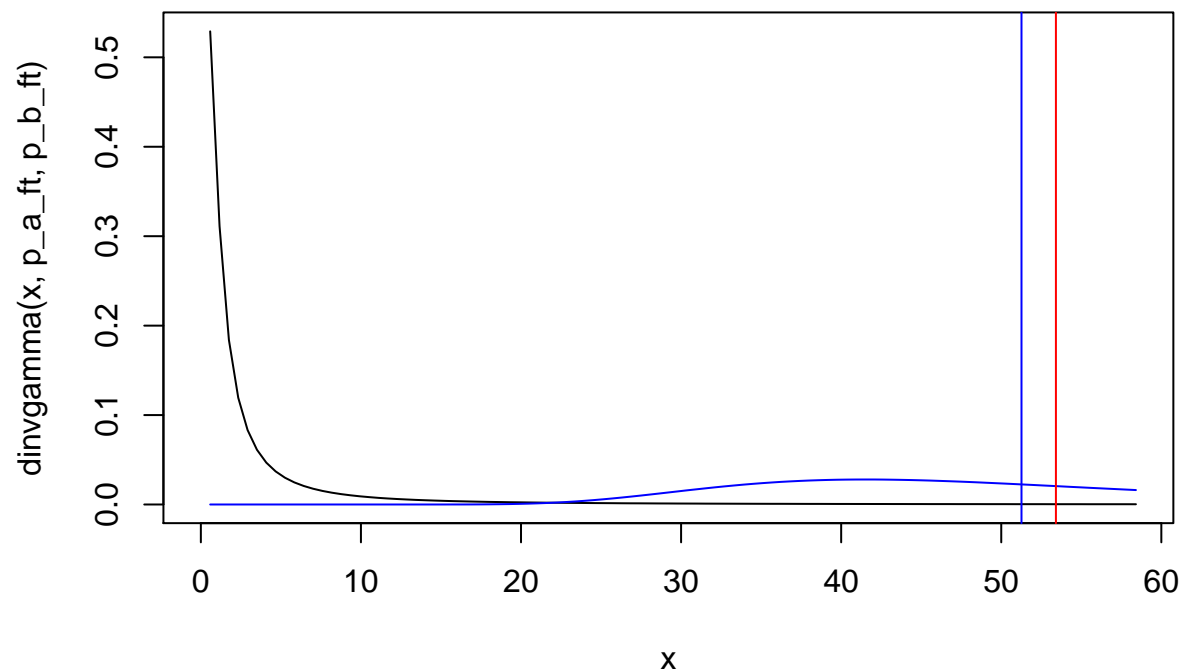
```



```

curve(dinvgamma(x,p_a_ft,p_b_ft), 0, true_sig_ft^2 +5, col='black')
curve(dinvgamma(x,po_a_ft,po_b_ft), 0, true_sig_ft^2 +5, add=T, col='blue')
abline(v=po_b_ft/(po_a_ft-1),col='blue')
abline(v=true_sig_ft^2,col='red')

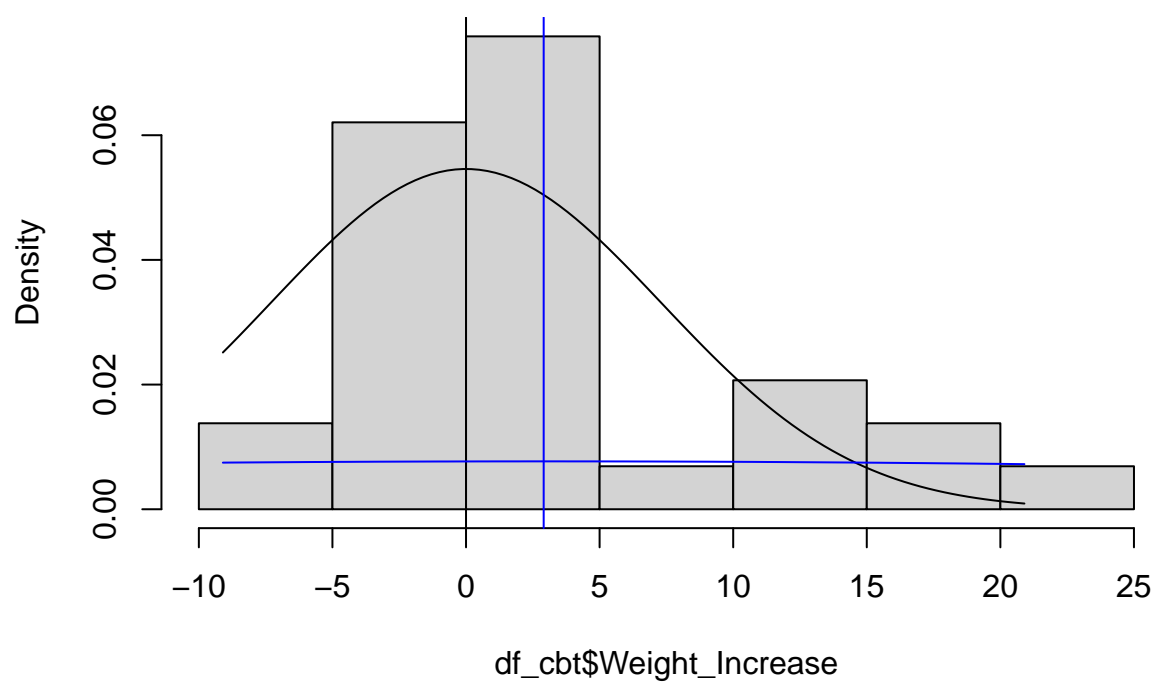
```



Next we plot the mean distributions.

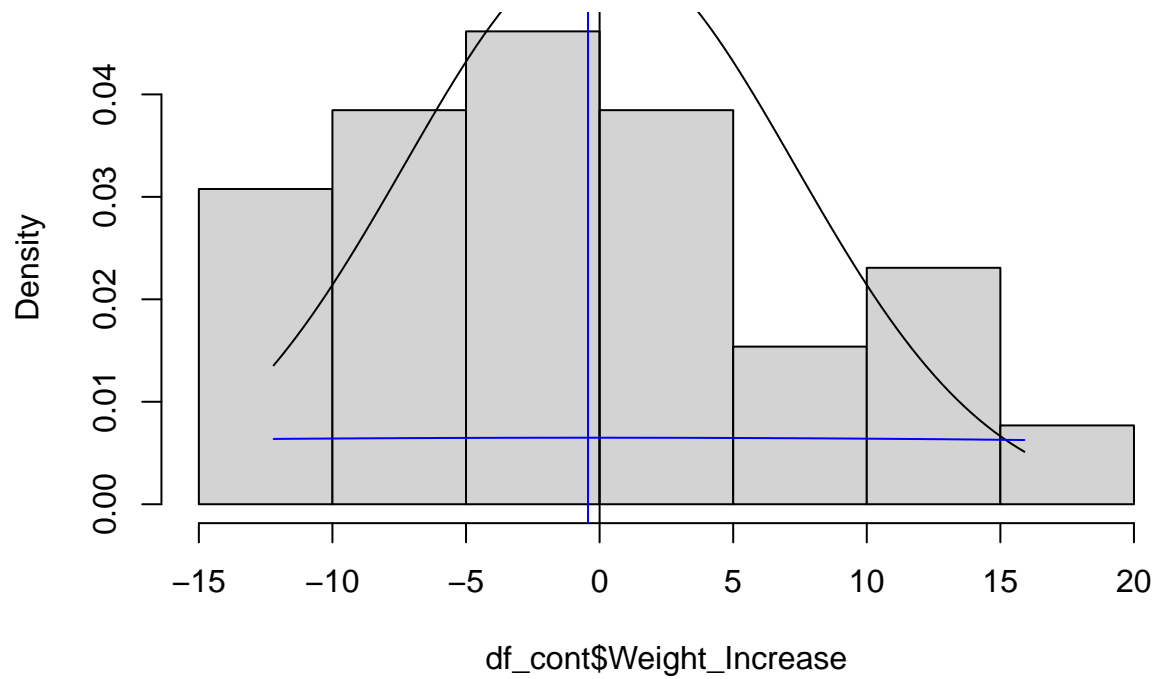
```
min_x <- min(df_cbt$Weight_Increase)
max_x <- max(df_cbt$Weight_Increase)
hist(df_cbt$Weight_Increase, freq=F)
curve(dnorm(x,mean=p_mu_cbt,sd=true_sig_cbt), min_x, max_x, add=T, col='black')
abline(v=prior_mu_cbt,col='black')
curve(dnorm(x,mean=po_mu_cbt,sd=po_b_cbt/(po_a_cbt-1)), min_x, max_x, add=T, col='blue')
abline(v=po_mu_cbt,col='blue')
```

Histogram of df_cbt\$Weight_Increase

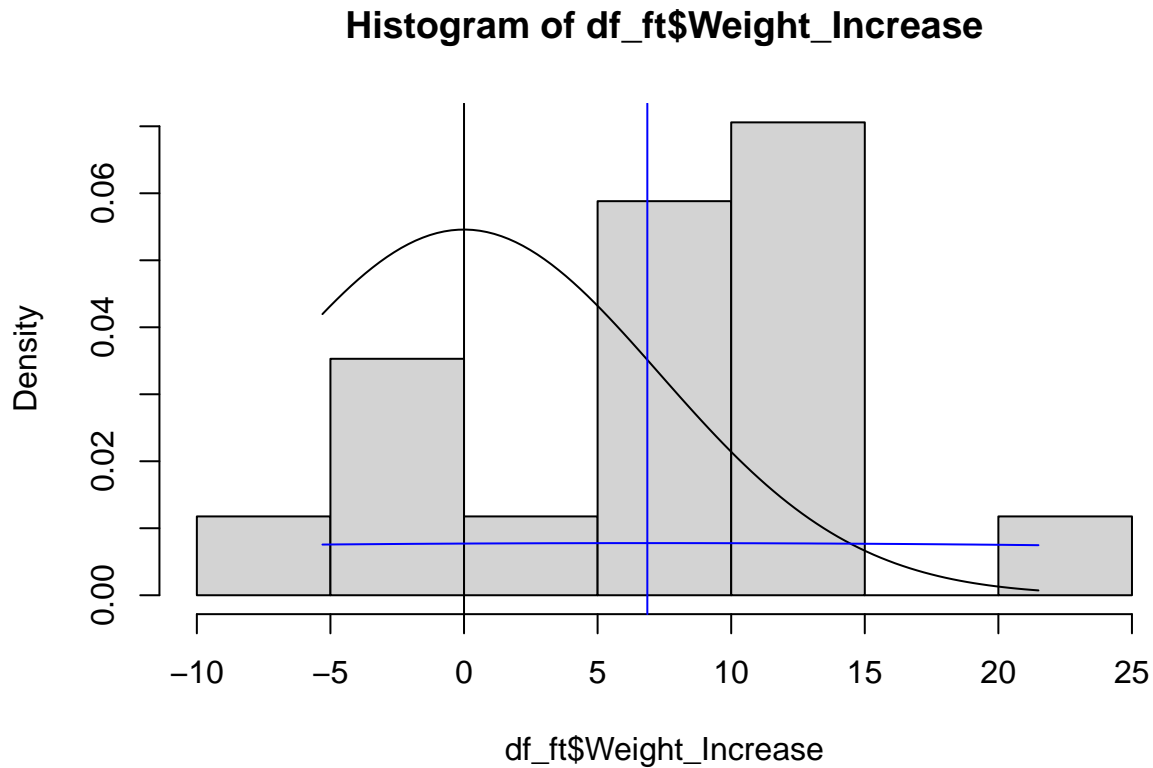


```
min_x <- min(df_cont$Weight_Increase)
max_x <- max(df_cont$Weight_Increase)
hist(df_cont$Weight_Increase, freq=F)
curve(dnorm(x,mean=p_mu_cont,sd=true_sig_cont), min_x, max_x, add=T, col='black')
abline(v=prior_mu_cont,col='black')
curve(dnorm(x,mean=po_mu_cont,sd=po_b_cont/(po_a_cont-1)), min_x, max_x, add=T, col='blue')
abline(v=po_mu_cont,col='blue')
```

Histogram of df_cont\$Weight_Increase



```
min_x <- min(df_ft$Weight_Increase)
max_x <- max(df_ft$Weight_Increase)
hist(df_ft$Weight_Increase, freq=F)
curve(dnorm(x,mean=p_mu_ft,sd=true_sig_ft), min_x, max_x, add=T, col='black')
abline(v=prior_mu_ft,col='black')
curve(dnorm(x,mean=po_mu_ft,sd=po_b_ft/(po_a_ft-1)), min_x, max_x, add=T, col='blue')
abline(v=po_mu_ft,col='blue')
```



We see the same exact results in the difference from prior to posterior for the variance parameter; however the results for the distribution of the mean parameter is much different. Before the distribution for the mean had a decreasing variance after adding samples, but this time the variance has a large increase. This comes from us no longer “knowing” the true variance. Since we do not have the variance fixed, we can only base the distribution of the mean based off the mean and variance that we observe and our observed variance was much higher than our prior beliefs, so the variance increase this time.

Part e

```
M <- 1000
c_val <- 0.05

samples_cbt <- rinvgamma(M, po_a_cbt, po_b_cbt)
samples_cont <- rinvgamma(M, po_a_cont, po_b_cont)
samples_ft <- rinvgamma(M, po_a_ft, po_b_ft)

prob_vec <- c(c_val, 1-c_val)
ci_cbt <- quantile(samples_cbt, probs=prob_vec)
ci_cont <- quantile(samples_cont, probs=prob_vec)
ci_ft <- quantile(samples_ft, probs=prob_vec)

print(paste0('CBT Cred Int: ', ci_cbt))

## [1] "CBT Cred Int: 33.4086195240715" "CBT Cred Int: 79.7162386135998"
```

```
print(paste0('Cont Cred Int: ', ci_cont))
```

```
## [1] "Cont Cred Int: 37.7962315640504" "Cont Cred Int: 91.7684173486601"
```

```
print(paste0('FT Cred Int: ', ci_ft))
```

```
## [1] "FT Cred Int: 28.5011054745794" "FT Cred Int: 86.893461386895"
```

Again we see the same credible intervals as problem 3, since variance is not based off our mean value.

```
M <- 1000
c_val <- 0.05

samples_cbt <- rnorm(M, po_mu_cbt, po_b_cbt / (po_a_cbt-1))
samples_cont <- rnorm(M, po_mu_cont, po_b_cont / (po_a_cont-1))
samples_ft <- rnorm(M, po_mu_ft, po_b_ft/(po_a_ft-1))

prob_vec <- c(c_val, 1-c_val)
ci_cbt <- quantile(samples_cbt, probs=prob_vec)
ci_cont <- quantile(samples_cont, probs=prob_vec)
ci_ft <- quantile(samples_ft, probs=prob_vec)
```

```
print(paste0('CBT Cred Int: ', ci_cbt))
```

```
## [1] "CBT Cred Int: -81.7599673938125" "CBT Cred Int: 86.2630257567716"
```

```
print(paste0('Cont Cred Int: ', ci_cont))
```

```
## [1] "Cont Cred Int: -101.194164003152" "Cont Cred Int: 105.686395305025"
```

```
print(paste0('FT Cred Int: ', ci_ft))
```

```
## [1] "FT Cred Int: -81.8304350417767" "FT Cred Int: 93.9792652578331"
```

We can see that due to the variance in our sample, if we don't hold our sample variance as the ground truth, then we have nowhere near enough evidence to make claims about what the mean should be. Compared to the value of weights a person could take on the values within our credible interval essentially say the true value is just about any weight gain/loss a person can endure.