

# Assignment 3

Terry Liu 1630005038

## Answer on Question One

(a) Since the prior distribution is Dirichlet distribution, the posterior distribution is also the Dirichlet distribution:  $p(\theta|y) = \text{Dirichlet}(y_1 + a_1 + \dots + y_n + a_n)$ . From the properties of the Dirichlet distribution, the marginal posterior distribution of  $(\theta_1, \theta_2, 1 - \theta_1 - \theta_2)$  is also Dirichlet:

$$p(\theta_1, \theta_2|y) = \frac{\Gamma(a_1 + a_2 + \dots + a_J)}{\Gamma(a_1)\Gamma(a_2)\dots\Gamma(a_J)} \theta_1^{y_1 + a_1 - 1} \theta_2^{y_2 + a_2 - 1} (1 - \theta_1 - \theta_2)^{y_{rest} + a_{rest} - 1}, \text{ where } y_{rest} = y_3 + \dots + y_J, a_{rest} = a_3 + \dots + a_J.$$

We can do a change of the variables to  $(\alpha, \beta) = (\frac{\theta_1}{\theta_1 + \theta_2}, \theta_1 + \theta_2)$ . The Jacobian of this transformation is  $[\frac{1}{\beta}]$ , so the transformed density is :

Since the posterior density divides into separate factors for  $\alpha$  and  $\beta$ , they are independent, so the posterior distribution is  $y \text{ textBeta}(y_1 + a_1, y_2, a_2)$ .

(b) The  $\text{Beta}(y_1 + a_1, y_2 + a_2)$  posterior distribution can also be derived from a  $\text{Beta}(a_1, a_2)$  prior distribution and a binomial observation  $y_1$  with sample size  $y_1 + y_2$ .

## Answer on Question Two

Assume independent uniform prior distributions on the multinomial parameters. Then the posterior distributions are independent multinomial:

and  $\alpha_1 = \frac{\pi_1}{\pi_1 + \pi_2}$ ,  $\alpha_2 = \frac{\pi_1^*}{\pi_1^* + \pi_2^*}$ . From the properties of the Dirichlet distribution:

The histogram of 2000 draws from the posterior density of  $2 - \alpha_1$  is attached, Based on this histogram, the posterior probability that there was a shift toward Bush is 19%

```
alpha.1 <- rbeta (2000, 295, 308)
alpha.2 <- rbeta (2000, 289, 333)
dif <- alpha.2 - alpha.1
hist (dif, xlab="alpha_2 - alpha_1", yaxt="n",
      breaks=seq(-.12,.08,.01), cex=2)
print (mean(dif>0))
```

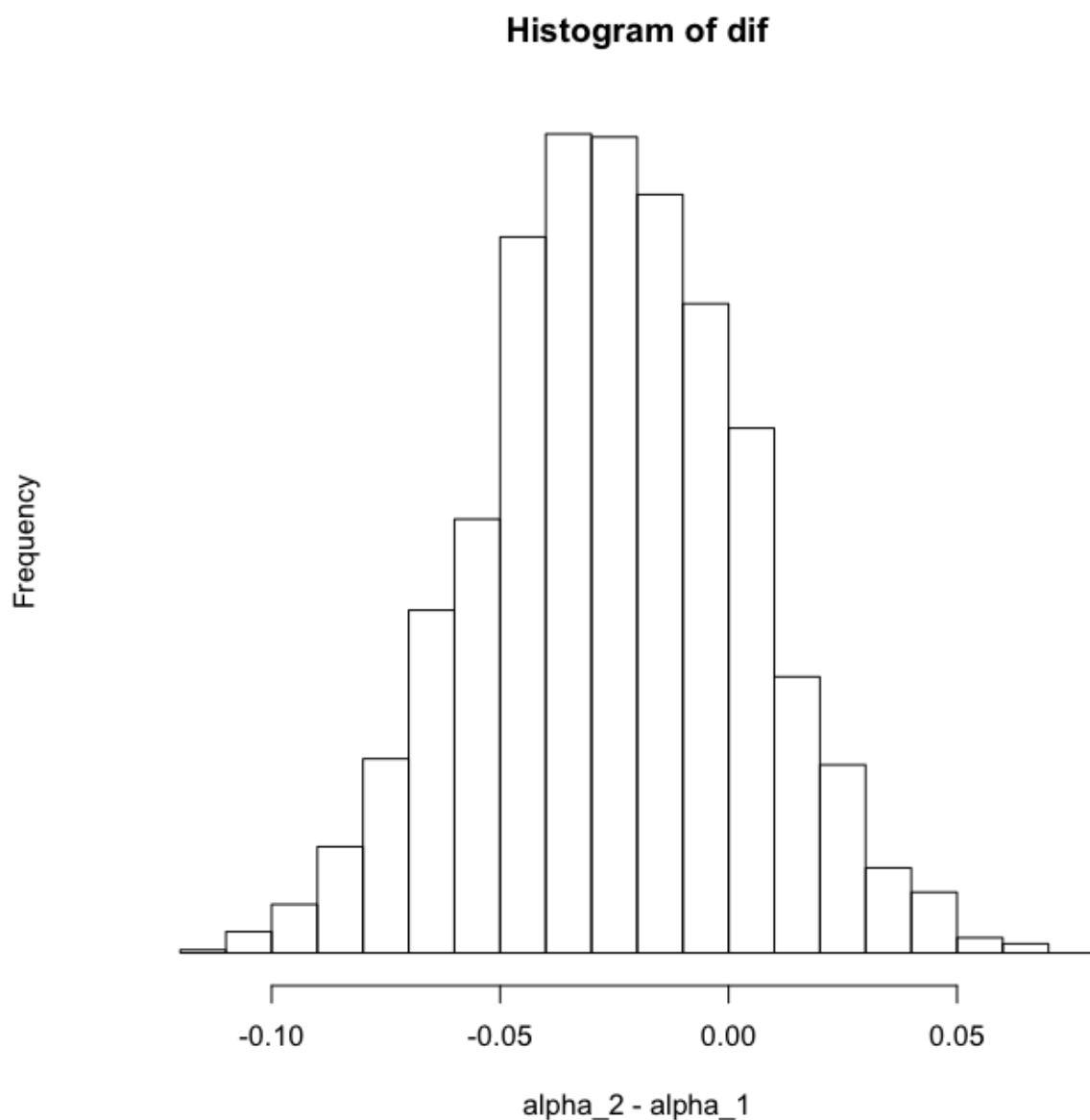


Figure 1:

### Answer of Question Three

Data distribution is  $p(y|\mu_c, \mu_t, \sigma_c, \sigma_t) = \prod_{i=1}^3 2N(y_{ci}|\mu_c, \sigma_c^2) \prod_{i=1}^3 6N(y_{ti}|\mu_t, \sigma_t^2)$ . Posterior distribution is  $p(y|\mu_c, \mu_t, \log\sigma_c, \log\sigma_t) = p(y|\mu_c, \mu_t, \log\sigma_c, \log\sigma_t)p(y|\mu_c, \mu_t, \log\sigma_c, \log\sigma_t)$

The posterior density factors, so  $(\mu_c, \sigma_c)$  are independent of  $(\mu_t, \sigma_t)$  in the posterior distribution. So, under this model, we can analyze the two experiments separately. We notice that the posterior distributions for  $\mu_c$  and  $\mu_t$  are:

We can use R to print the plot:

```

mu.c <- 1.013 + (0.24/sqrt(32))*rt(1000,31)
mu.t <- 1.173 + (0.20/sqrt(36))*rt(1000,35)
dif <- mu.t - mu.c
hist (dif, xlab="mu_t - mu_c", yaxt="n", breaks=seq(-.1,.4,.02), cex=2)
print (sort(dif)[c(25,976)])

```

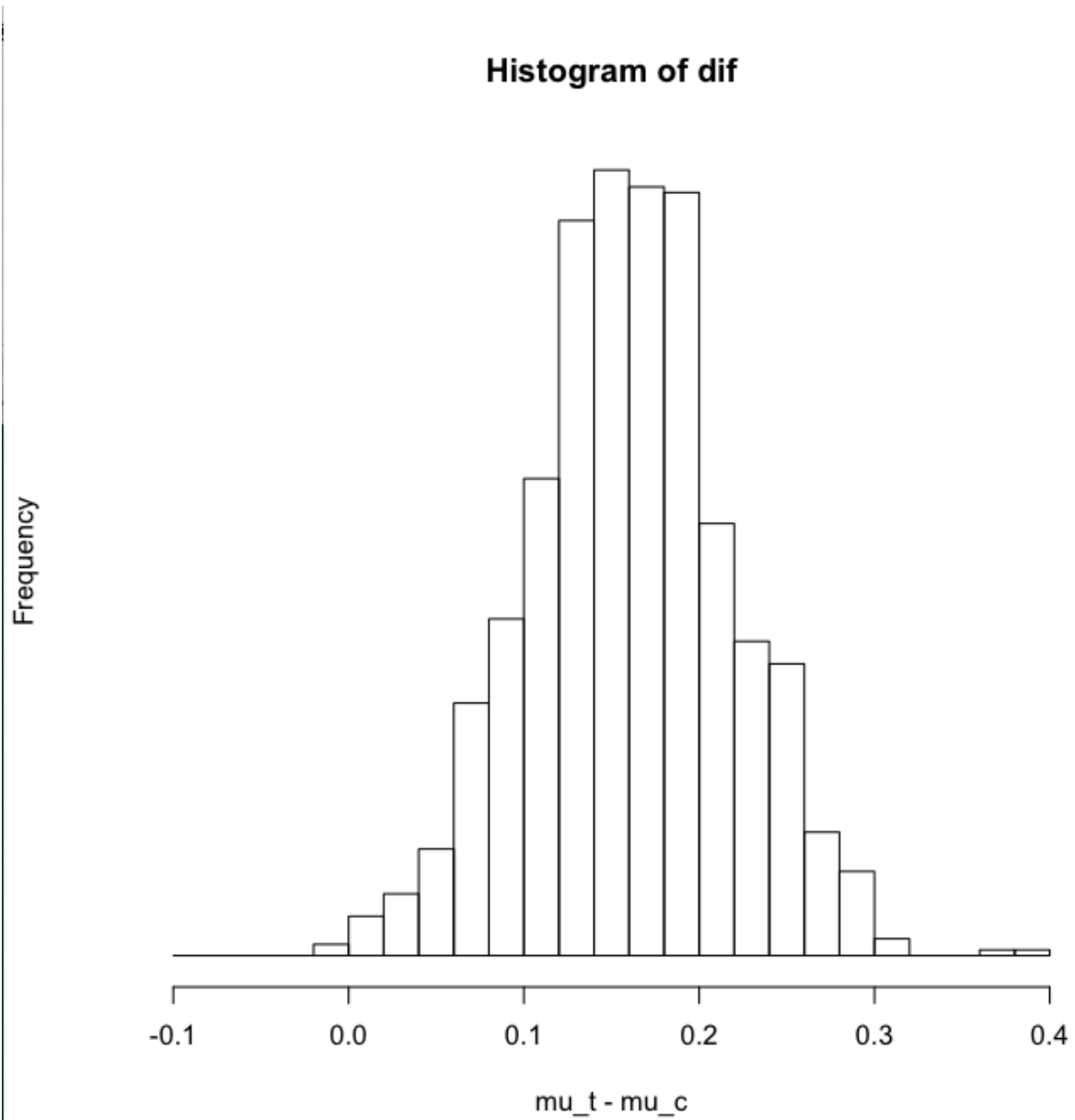


Figure 2: