

3.14

a)

$$\begin{aligned}
 p(y|\theta) &= \theta^y (1 - \theta)^{(n-y)} \\
 \log[p(\theta|y)] &= \sum \log[p(y|\theta)] = y \log[\theta] + (n - y) \log[1 - \theta] \\
 \frac{d \log[p(\theta|y)]}{d\theta} &= \frac{y}{\theta} + \frac{n - y}{1 - \theta} \\
 \text{MLE estimate : } 0 &= \frac{y}{\theta} + \frac{n - y}{1 - \theta} \\
 \frac{n}{y} &= \frac{1}{\theta} \\
 \theta &= \frac{y}{n} \\
 \frac{d^2 \log[p(\theta|y)]}{d\theta^2} &= \frac{y}{\theta^2} + \frac{(n - y)}{(1 - \theta)^2} \\
 J(\theta) &= -\frac{y}{\theta^2} - \frac{(n - y)}{(1 - \theta)^2}
 \end{aligned}$$

b)

$$\begin{aligned}
 p_u(\theta) &= \theta^y (1 - \theta)^{(n-y)} / \exp[n] \\
 -\frac{d^2 P_u(\theta)}{d\theta^2} &= -\frac{y}{n\theta^2} - \frac{n - y}{n(1 - \theta)^2}
 \end{aligned}$$

c)

$$p_u(\theta|y) = \theta^y (1 - \theta)^{n-y} \left[-\frac{y}{n\theta^2} - \frac{n - y}{n(1 - \theta)^2} \right]$$

No because it no longer retains the form of the binomial density function

d)

$$\begin{aligned}
 p(y|\theta) &= \prod_{i=1}^n \frac{e^{-\theta} \theta^y}{y!} \\
 &= \frac{e^{-n\theta} \theta^y}{y!} \\
 l p(\theta|y) &= y \log[\theta] - n\theta \\
 \frac{l p(\theta|y)}{d\theta} &= \frac{y}{\theta} - n \\
 \text{MLE : } 0 &= \frac{y}{\theta} - n \rightarrow \theta = \frac{y}{n} \\
 -\frac{d^2 l p(\theta|y)}{d\theta^2} &= -\frac{y}{\theta^2} \\
 p_u(\theta) &= \frac{e^{-n\theta} \theta^y}{y!} / n \\
 &= \exp\left[\frac{y}{n}\right] \theta - \theta \\
 \frac{d^2 \log[p(\theta|y)]}{d\theta^2} &= \frac{y}{n\theta} - 1 \\
 p_u(\theta|y) &= \frac{e^{-n\theta} \theta^{y-1}}{y!} - 1
 \end{aligned}$$

Yes because it still maintains the general form of the poisson density function

4.1

Posterior Distributions: $P(\theta_1|Y_1 = 57) = \text{beta}(58, 47)$

$P(\theta_2|Y_2 = 30) = \text{beta}(31, 21)$

```
theta.1 = rbeta(n = 5000, shape1 = 58, shape2 = 44)
```

```
theta.2 = rbeta(n = 5000, shape1 = 31, shape2 = 21)
```

```
## Estimated Probability that theta.1 < theta.2
```

```
length(which(theta.1/theta.2 < 1) == TRUE) / 5000
```

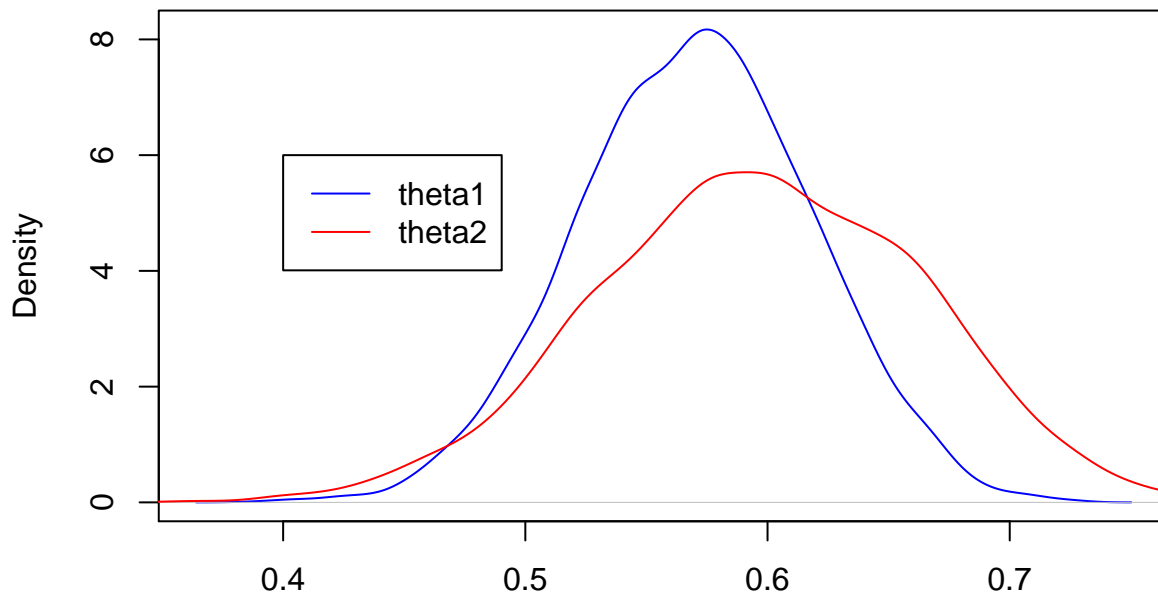
```
[1] 0.6214
```

```
plot(density(theta.1), col = "blue", main = "Posterior Simulation Comparison")
```

```
lines(density(theta.2), col = "red")
```

```
legend(x = .4, y = 6, legend = c("theta1", "theta2"), lty = c(1,1), col = c("blue", "red"))
```

Posterior Simulation Comparison



N = 5000 Bandwidth = 0.007935

4.2

a)

$$P(\theta_a|Y_a) = P(Y_a|\theta)P(\theta) = \text{Poisson}(Y_a/N|\theta)\text{Gamma}(120,10) = \text{Gamma}(120 + 237, 10 + 10)$$
$$P(\theta_b|Y_b) = P(Y_b|\theta)P(\theta) = \text{Poisson}(Y_b/N)\text{Gamma}(12,1) = \text{Gamma}(12 + 125, 1 + 13)$$

```
Y.a = c(12, 9, 12, 14, 13, 13, 15, 8, 15, 6)
```

```
Y.b = c(11, 11, 10, 9, 9, 8, 7, 10, 6, 8, 8, 9, 7)
```

```
theta.a = rgamma(n = 100000, shape = 120 + sum(Y.a), rate = 10 + 10)
```

```
theta.b = rgamma(n = 100000, shape = 12 + sum(Y.b), rate = 1 + 13)
```

```
## Probability that theta.a is > theta.b
```

```
mean(theta.a > theta.b)
```

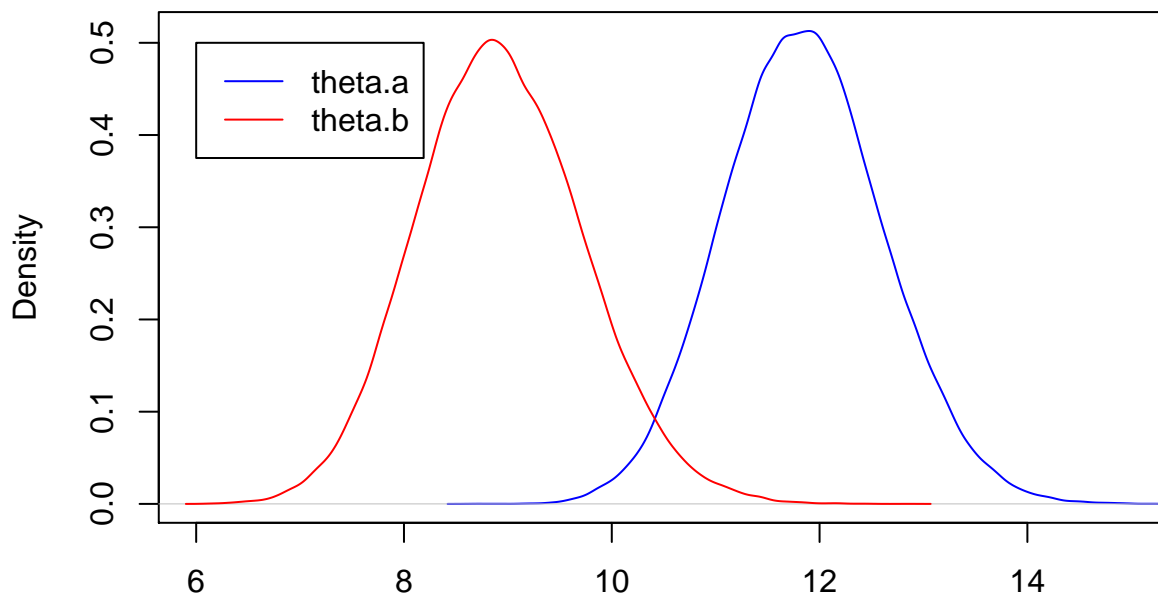
```
[1] 0.99494
```

```
plot(density(theta.a), col = "blue", main = "Posterior Simulation Comparison",  
      xlim = c(6, 15))
```

```
lines(density(theta.b), col = "red")
```

```
legend(x = 6, y = .5, legend = c("theta.a", "theta.b"), lty = c(1,1), col = c("blue", "red"))
```

Posterior Simulation Comparison



N = 100000 Bandwidth = 0.06944

b)

```
results = data.frame()

n = 20; sims = 100000

for (i in 1:n) {
  theta.a = rgamma(n = sims, shape = 120, rate = 10)
  theta.b = rgamma(n = sims, shape = 12 * i, rate = i)

  x = mean(theta.a < theta.b)

  results = rbind(results, data.frame(N = i, Prob = x))
}

## The Probability of N where Theta.b < Theta.a ~ 10+
t(round(results, 4))
```

	1	2	3	4	5	6	7	8	9
N	1.0000	2.0000	3.0000	4.0000	5.0000	6.0000	7.0000	8.0000	9.0000
Prob	0.4691	0.4826	0.4841	0.4892	0.4934	0.4939	0.4973	0.4985	0.4991

	10	11	12	13	14	15	16	17
N	10.0000	11.0000	12.0000	13.0000	14.0000	15.0000	16.0000	17.0000
Prob	0.4984	0.5034	0.4977	0.4999	0.5048	0.5046	0.5022	0.5048

	18	19	20
N	18.0000	19.0000	20.0000
Prob	0.4988	0.5046	0.503

c)

```
theta.a = rgamma(n = sims, shape = 120, rate = 10 + 10)
theta.b = rgamma(n = sims, shape = 12 + sum(Y.b), rate = 1 + 13)

pois.a = rpois(n = sims, lambda = theta.a)
pois.b = rpois(n = sims, lambda = theta.b)

mean(pois.b < pois.a)

[1] 0.19368

results = data.frame()

sims = 100000

for (i in seq(.0, 2, .05)) {

  theta.a = rgamma(n = sims, shape = 120, rate = 10 + 10)
```

```

theta.b = rgamma(n = sims, shape = 12 * i, rate = i)

pois.a = rpois(n = sims, lambda = theta.a)
pois.b = rpois(n = sims, lambda = theta.b)

x = mean(pois.b < pois.a)

results = rbind(results, data.frame(N = i, Prob = x))

}

## The Probability of N where Theta.b < Theta.a for approximately all N
t(round(results, 4))

```

	1	2	3	4	5	6	7	8	9	10
N	0.000	0.0500	0.1000	0.15	0.2000	0.2500	0.3000	0.3500	0.4000	0.4500
Prob	0.997	0.4542	0.3396	0.28	0.2404	0.2123	0.1933	0.1797	0.1665	0.1546
	11	12	13	14	15	16	17	18	19	20
N	0.50	0.5500	0.6000	0.6500	0.7000	0.7500	0.800	0.8500	0.9000	0.9500
Prob	0.15	0.1408	0.1373	0.1319	0.1257	0.1227	0.121	0.1157	0.1134	0.1119
	21	22	23	24	25	26	27	28	29	30
N	1.0000	1.050	1.1000	1.1500	1.2000	1.2500	1.3000	1.3500	1.4000	1.4500
Prob	0.1088	0.106	0.1049	0.1034	0.1007	0.0991	0.0976	0.0983	0.0949	0.0953
	31	32	33	34	35	36	37	38	39	40
N	1.5000	1.5500	1.6000	1.6500	1.7000	1.7500	1.8000	1.8500	1.9000	1.9500
Prob	0.0942	0.0932	0.0911	0.0903	0.0901	0.0892	0.0882	0.0888	0.0851	0.0857
	41									
N	2.0000									
Prob	0.0858									

4.8

a)

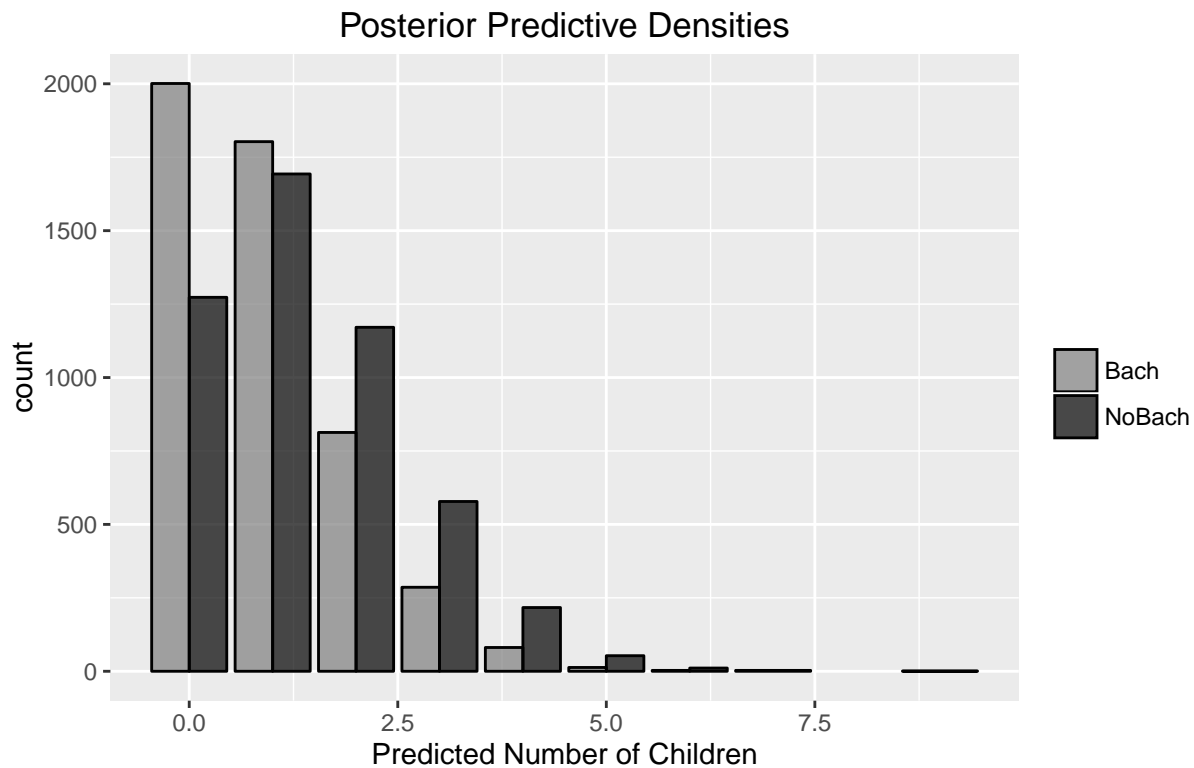
```
prior.theta.shape = 2; prior.theta.rate = 1

post.theta.a = rgamma(5000, shape = prior.theta.shape + sum(bach),
                      rate = prior.theta.rate + length(bach))
post.theta.b = rgamma(5000, shape = prior.theta.shape + sum(nobach),
                      rate = prior.theta.rate + length(nobach))

pred.theta.a = rpois(n = 5000, lambda = post.theta.a)
pred.theta.b = rpois(n = 5000, lambda = post.theta.b)

dta = data.frame(
  Theta = c(rep("A", 5000), rep("B", 5000)),
  Pred = c(pred.theta.a, pred.theta.b)
)

ggplot(dta) +
  geom_bar(aes(x = Pred, fill = Theta), position = "dodge", alpha = .7, color = "black") +
  scale_x_continuous("Predicted Number of Children") +
  scale_fill_manual("", labels = c("Bach", "NoBach"), values = c("gray50", "black")) +
  ggtitle("Posterior Predictive Densities")
```



b)

Since the 95% Confidence Interval of the difference in the posterior distributions does not include 0 we could conclude that there are significant differences between two distributions. The 95% Confidence intervals of the difference in posterior predictive distributions does however contain 0 so we not be able to say that these two distributions are significantly different.

```
## Difference in Posterior Theta Estimate  
quantile(post.theta.b - post.theta.a, c(.025, .975))
```

```
      2.5%      97.5%  
0.1503111 0.7355482
```

```
## Difference in Posterior Prediction Estimate  
quantile(pred.theta.b - pred.theta.a, c(.025, .975))
```

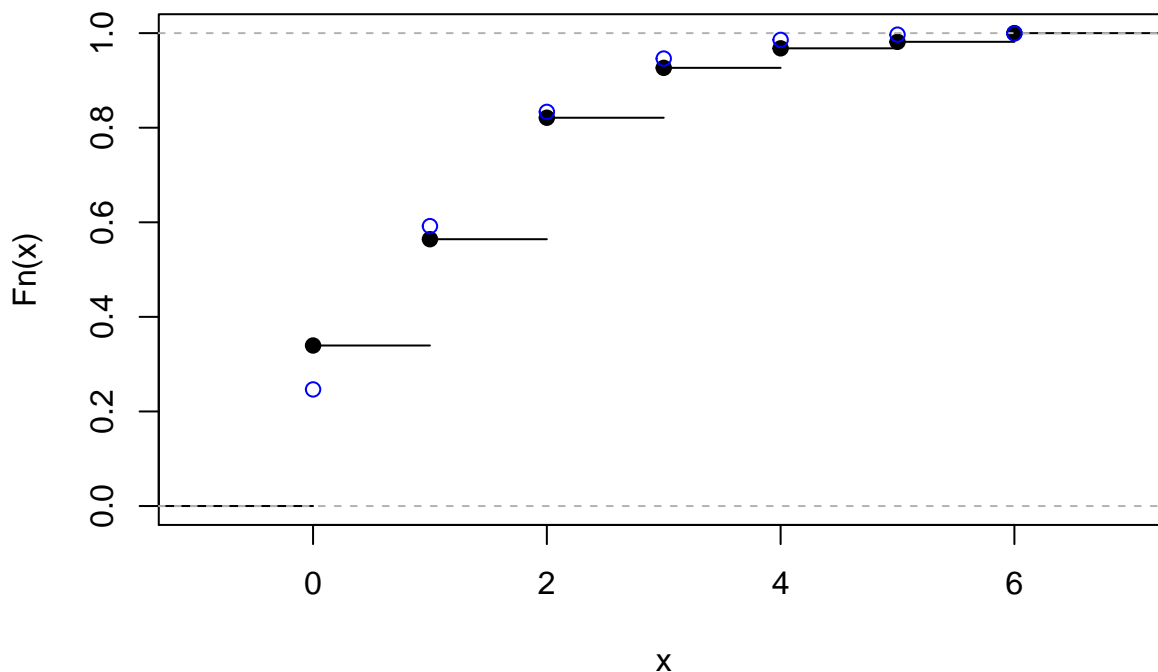
```
      2.5% 97.5%  
      -3      4
```

c)

The Poisson(1.4) appears to be a good model for approximating the distribution of the NoBach data set. Except for $Y = 0$, all of the ECDF points are very close to the points of of the poisson density.

```
plot(ecdf(nobach), main = "NoBach ECDF vs Pois(1.4)")  
points(x = 0:6, ppois(q = 0:6, lambda = 1.4), col = "blue")
```

NoBach ECDF vs Pois(1.4)



d)

The plot supports the poisson model as an appropriate model for the data. The average count of NoBach that have one child is higher than the those with no children which is consistent with the sampled data and with the distribution function of the Poisson(1.4) model used in the last section. I would expect Ones to be closer than Zero because its most likely closer to the true average.

```
results = data.frame()

for (i in 1:5000) {
  y = pred.theta.b[sample(x = 5000, size = 218)]

  zero = length(which(y == 0))
  ones = length(which(y == 1))

  results = rbind(results, data.frame(zero = zero, ones = ones))
}

ggplot(results) +
  geom_point(aes(x = zero, y = ones)) +
  geom_vline(xintercept = mean(results$zero), lty = 2, color = "blue") +
  geom_hline(yintercept = mean(results$ones), lty = 2, color = "blue") +
  ggtitle("Comparison of Theta_B Posterior Predictive Sampling")
```

