

Gibbs Samplers

Jonathan Navarrete

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Introduction

Now that we've familiarized ourselves with MCMC and the Metropolis-Hastings algorithms, we begin to analyze a now-common MCMC algorithm called Gibbs sampler. The Gibbs sampler is in fact a special case of the Metropolis-Hastings algorithm for high dimensional target distributions.

We introduce the Gibbs sampler with a two-stage example. The **two-state Gibbs sampler algorithm** as described Robert & Casella goes as follows

Take $X_0 = x_0$

For $t = 1, 2, \dots$, generate

1. $y_i \sim f_{Y|X}(\cdot|x_{t-1})$
2. $X_t \sim f_{X|Y}(\cdot|y_t)$

The *two-stage* Gibbs sampler creates a Markov chain from a joint distribution in the following way. If two random variables X and Y have joint density $f(x, y)$, with corresponding conditional densities $f_{Y|X}$ and $f_{X|Y}$, the two stage Gibbs sampler generates a Markov chain (X_t, y_i) by generating y_i from conditional density $f_{Y|X}$ and then generating X_t from conditional density $f_{X|Y}$.

We illustrate the implementation of the Gibbs sampler with a simple example. Consider a bivariate Normal distribution where

$$X, Y \sim N_2 \left(\begin{pmatrix} \mu_X \\ \mu_Y \end{pmatrix}, \begin{pmatrix} \sigma_X^2 & \sigma_{XY}^2 \\ \sigma_{YX}^2 & \sigma_Y^2 \end{pmatrix} \right)$$

The marginal distributions of X and Y are $N(\mu_X, \sigma_X)$ and $N(\mu_Y, \sigma_Y)$. The conditional distributions of Y and X are

$$Y|X = x \sim N \left(\mu_Y + \frac{\rho\sigma_Y}{\sigma_X}(x - \mu_X), (1 - \rho^2)\sigma_Y^2 \right)$$

and

$$X|Y = y \sim N \left(\mu_X + \frac{\rho\sigma_X}{\sigma_Y}(y - \mu_Y), (1 - \rho^2)\sigma_X^2 \right)$$

ρ is the correlation between X and Y , and $(1 - \rho^2)\sigma_X^2$ is the variance.

```
N = 10000

rho = 0.9
mu_x = 1
mu_y = 2
sd_x = 1.2
sd_y = 0.75

s1 = sqrt(1 - rho^2) * sd_x
s2 = sqrt(1 - rho^2) * sd_y

MVN = matrix(data = NA, nrow = N, ncol = 2,
              dimnames = list(NULL, c("X", "Y")))
```

```

MVN[1, ] = c(mu_x, mu_y)
Y = MVN[1, 2] ## get Y vals
for(i in 1:(N-1)){
  mx = mu_x + rho * (Y - mu_y) * sd_x/sd_y
  X = rnorm(n = 1, mx, s1)
  MVN[i+1, 1] = X
  my = mu_y + rho * (X - mu_x) * sd_y/sd_x
  Y = rnorm(n = 1, mean = my, sd = s2)
  MVN[i+1, 2] = Y
}

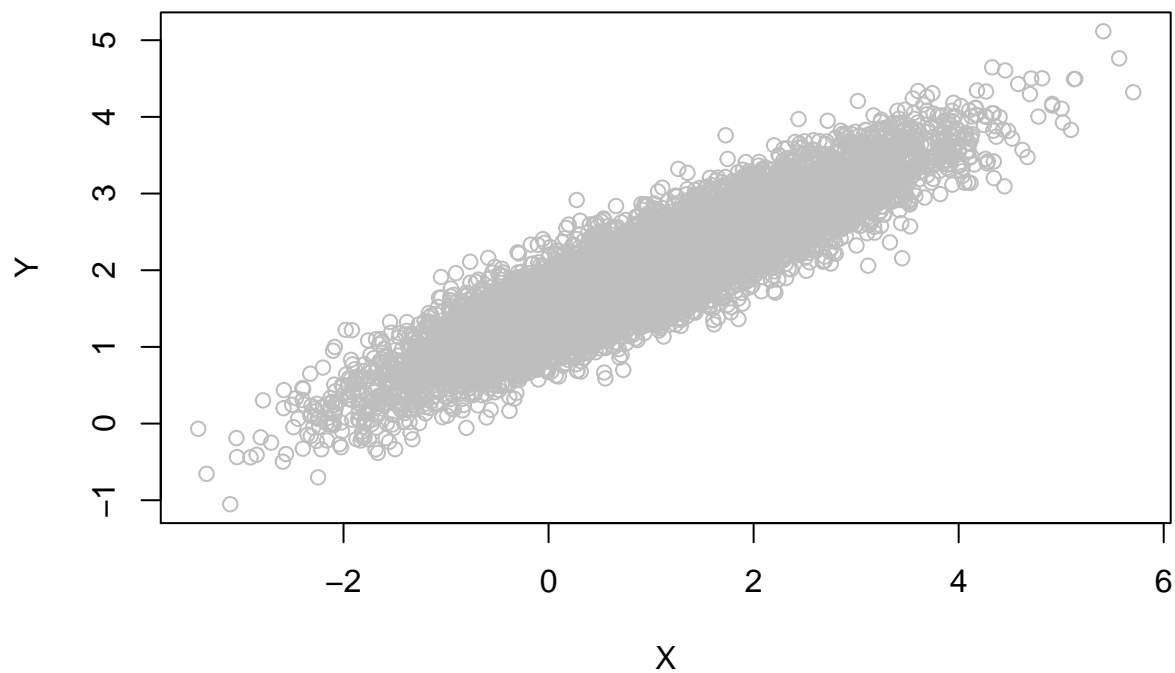
```

```

plot(MVN, type = "p", col = 8,
     main = "MVN samples")

```

MVN samples



```

## means
colMeans(MVN)

```

```

##      X      Y
## 1.005383 2.007809

```

```

## correlation
cor(MVN)

```

```

##      X      Y
## X 1.0000000 0.9014338
## Y 0.9014338 1.0000000

```

Beta-Binomial revisited

In the introduction to these notes, we saw a Bayesian example of the Beta-Binomial distribution. From Casella's paper *Explaining the Gibbs Sampler*, we revisit this example.

$$X|\theta \sim \text{Bin}(n, \theta), \text{ and } \theta \sim \text{Beta}(a, b)$$

have joint density

$$f(x, \theta) = \binom{n}{x} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} \theta^{x+a-1} (1-\theta)^{n-x+b-1}$$

is the a $\text{Beta}(x+a, n-x+b)$ distribution.

Suppose we are interested in calculating some characteristics of the marginal distributions of $X|\theta$ and $\theta|a, b, x, n$.

$$f(x|\theta) \text{ is } \text{Bin}(n, \theta) f(\theta|x) \text{ is } \text{Beta}(x+a, n-x+b)$$

Therefore, we follow an iterative algorithm of

$$X_i \sim f(x|\theta) Y_{i+1} \sim f(y|X_i = x_i)$$

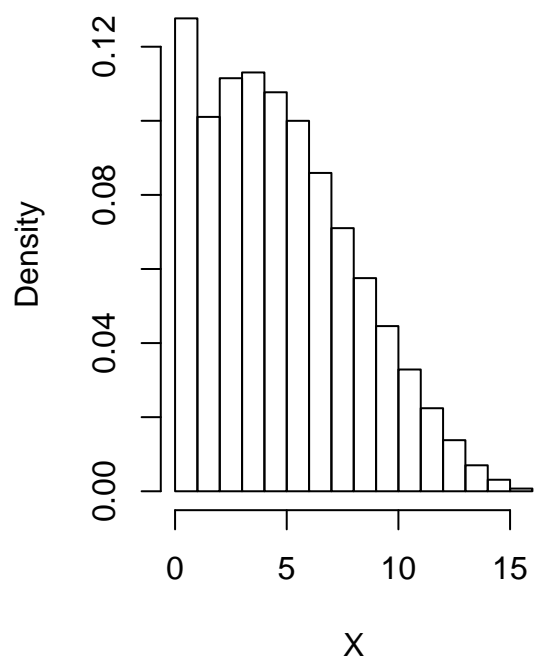
```
N = 10^5
n = 16
a = 2
b = 4
X = numeric(N)
Y = numeric(N)

## initial values
X[1] = 0.2
Y[1] = 0.34 ## theta values

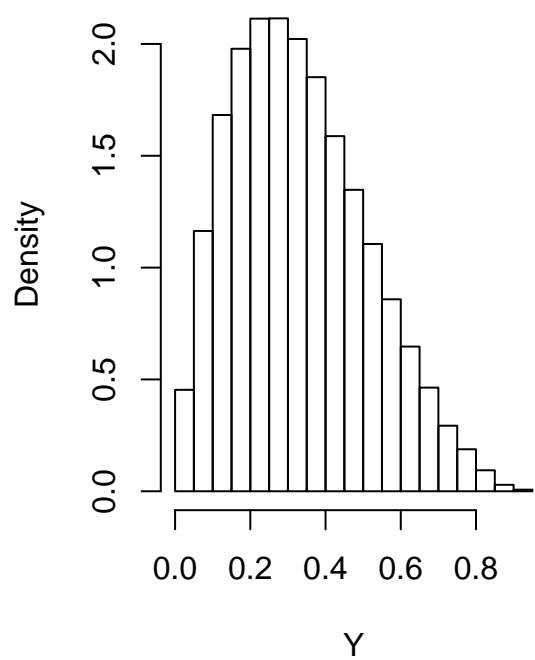
for(i in 1:N){
  X[i+1] = rbinom(n = 1, size = n, prob = Y[i])
  Y[i+1] = rbeta(1, a + X[i+1], n - X[i+1]+b)
}

par(mfrow = c(1,2))
hist(X, main = "Marginal Dist: X", probability = TRUE)
hist(Y, main = "Marginal Dist: X", probability = TRUE)
```

Marginal Dist: X



Marginal Dist: X



Poisson-Gamma Model

Consider a random sample $\mathbf{y} = (y_1, \dots, y_n)^T$ where $y_i|\theta \sim \text{Poisson}(\theta)$ where $\theta \sim \text{Gamma}(\alpha, \beta)$ for $i \in 1, \dots, k$. Assume t and α are known constants, but that β has a $\text{Gamma}(c, d)$ hyperprior with known hyperparameters c and d . This represents a three stage model where the likelihood, prior and hyperprior are defined as

$$f(y_i|\theta) = \frac{\theta^{y_i}}{y_i!} e^{-\theta}, y_i \geq 0, \theta_i > 0$$

$$g(\theta|\beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta}, \alpha > 0, \beta > 0$$

$$h(\beta) = \frac{d^c}{\Gamma(c)} \beta^{c-1} e^{-d\beta}, c > 0, d > 0$$

Suppose our interest is in generating samples from the marginal posterior distributions of θ , $p(\theta|\mathbf{y})$. Note that while the gamma prior is conjugate with the Poisson likelihood and the gamma hyperprior is conjugate with the gamma prior, no closed form for $p(\theta|\mathbf{y})$ exists. However, the full conditional distributions of β and the θ needed to implement the Gibbs sampler can be extracted from the full conditional $p(\theta|\mathbf{y})$

$$\begin{aligned} p(\theta|\mathbf{y}, \beta) &\propto \prod_{i=1}^n f(y_i|\theta) g(\theta|\beta) \\ &\propto \theta^{n\bar{y}} e^{n\theta} \times \theta^{\alpha-1} e^{-\theta\beta} \\ &\propto \theta^{n\bar{y}+\alpha-1} e^{-\theta(n+\beta)} \\ &\propto \text{Gamma}(\theta|n\bar{y} + \alpha, n + \beta) \end{aligned}$$

while for β we have

$$\begin{aligned} p(\beta|\theta, \mathbf{y}) &\propto g(\theta|\beta) \times h(\beta) \\ &= \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \times \frac{d^c}{\Gamma(c)} \beta^{c-1} e^{-d\beta} \\ &\propto \beta^{\alpha+c-1} e^{-\beta(\theta+d)} \\ &\propto \text{Gamma}(\alpha + c, \theta + d) \end{aligned}$$

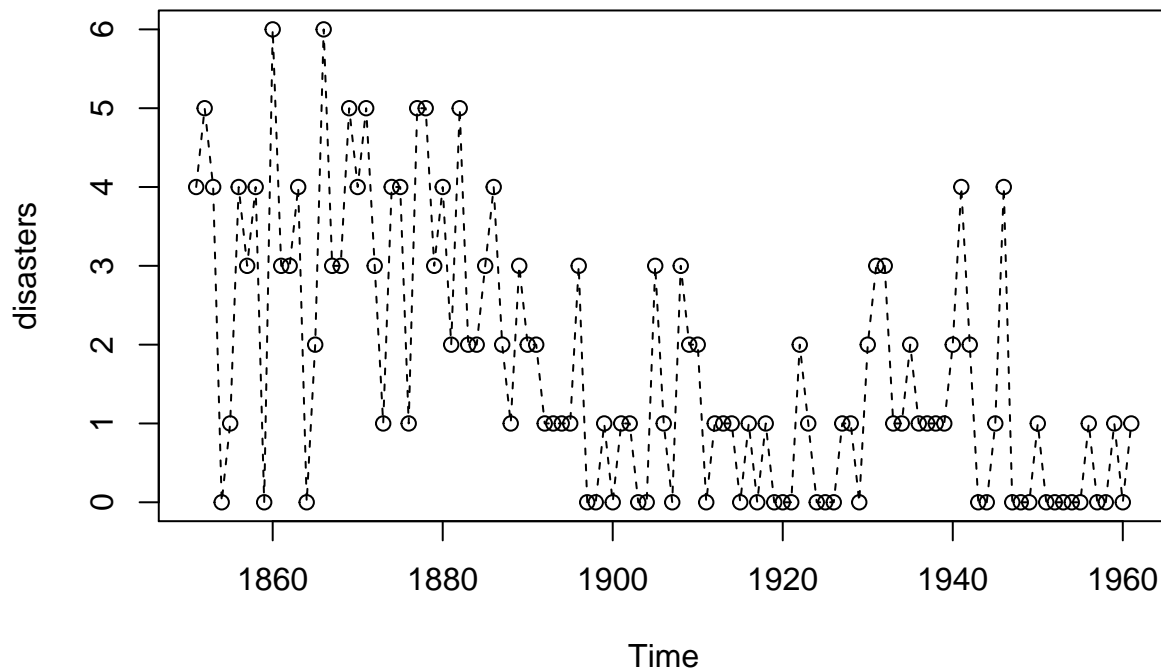
Example: Inferring patterns in UK coal mining disasters

Let's try to model a more interesting example, a time series of recorded coal mining disasters in the UK from 1851 to 1962. Occurrences of disasters in the time series is thought to be derived from a Poisson process with a large rate parameter in the early part of the time series, and from one with a smaller rate in the later part. We are interested in locating the change point in the series, which perhaps is related to changes in mining safety regulations.

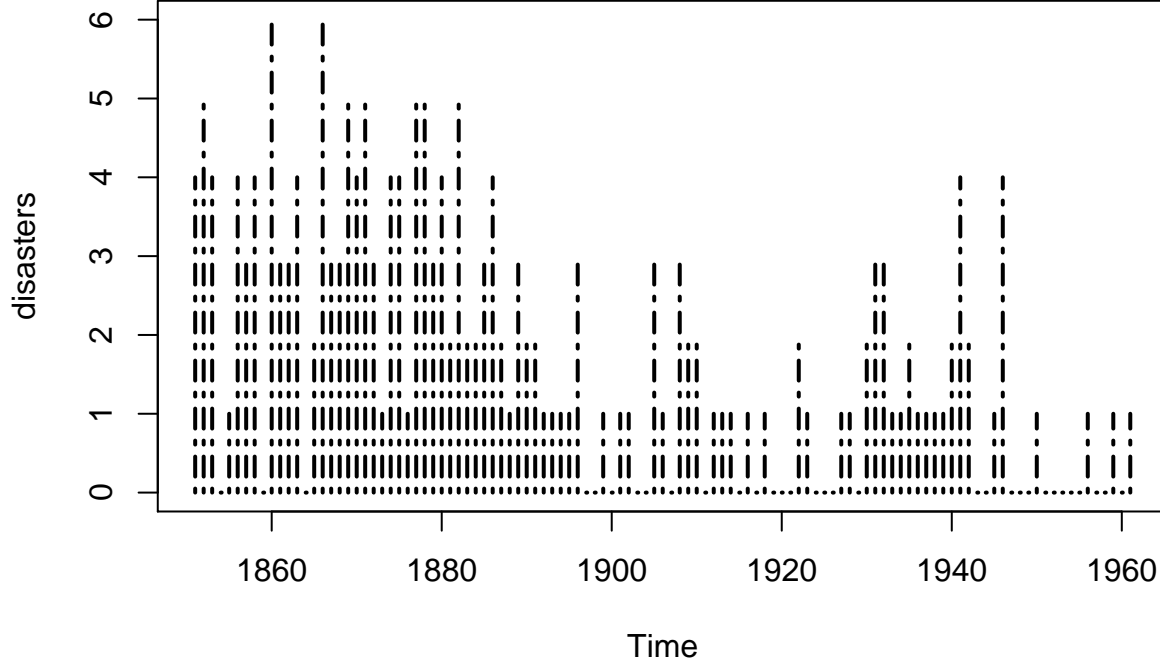
```
data_vector = c(4, 5, 4, 0, 1, 4, 3, 4, 0, 6, 3, 3, 4, 0, 2, 6,
                3, 3, 5, 4, 5, 3, 1, 4, 4, 1, 5, 5, 3, 4, 2, 5,
                2, 2, 3, 4, 2, 1, 3, 2, 2, 1, 1, 1, 1, 3, 0, 0,
                1, 0, 1, 1, 0, 0, 3, 1, 0, 3, 2, 2, 0, 1, 1, 1,
                0, 1, 0, 1, 0, 0, 0, 2, 1, 0, 0, 0, 1, 1, 0, 2,
                3, 3, 1, 1, 2, 1, 1, 1, 1, 2, 4, 2, 0, 0, 1, 4,
                0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1)

disasters = ts(data_vector, freq=1, start = 1851)

plot(disasters, type = "o", lty = 2)
```



```
plot(disasters, type = "h", lty = 6, lwd = 2)
```



We are going to use Poisson random variables for this type of count data. Denoting year i 's accident count by y_i ,

$$y_i \sim \text{Poisson}(\lambda)$$

The modeling problem revolves around estimating the values of the λ parameters. Looking at the time series above, it appears that the rate declines later in the time series. A changepoint model identifies a point (year) during the observation period (call it k) after which the parameter λ drops to a lower value. So we are estimating two λ parameters: one for the early period and another for the late period.

$$\lambda = \begin{cases} \theta & \text{if } i < k \\ \lambda & \text{if } i \geq k \end{cases}$$

We need to assign prior probabilities to both θ and λ parameters. The gamma distribution not only provides a continuous density function for positive numbers, but it is also conjugate with the Poisson sampling distribution.

We will specify suitably vague hyperparameters, letting $\alpha = 1$ and allowing β s to vary.

$$\begin{aligned} \theta &\sim \text{Gamma}(1, b_1) \\ \lambda &\sim \text{Gamma}(1, b_2) \end{aligned}$$

Since we do not have any intuition about the location of the changepoint (prior to viewing the data), we will assign a discrete uniform prior over all years 1851-1962.

$$k \sim \text{Unif}(1851, 1962)$$

$$\Rightarrow p(K = k) = \frac{1}{111}$$

Implementing Gibbs sampling We are interested in estimating the joint posterior of θ , λ and k given the array of annual disaster counts \mathbf{y} . This gives:

$$p(\theta, \lambda, k | \mathbf{y}) \propto p(\mathbf{y} | \theta, \lambda, k) p(\theta, \lambda, k)$$

To employ Gibbs sampling, we need to factor the joint posterior into the product of conditional expressions:

$$p(\theta, \lambda, k | \mathbf{y}) \propto p(y_{i < k} | \theta, k) p(y_{i \geq k} | \lambda, k) p(\theta) p(\lambda) p(k)$$

which we have specified as:

$$\begin{aligned} p(\theta, \lambda, k | \mathbf{y}) &\propto \left[\prod_{t=1851}^k \text{Poisson}(y_i | \theta) \times \prod_{t=k+1}^{1962} \text{Poisson}(y_i | \lambda) \right] \times \text{Gamma}(\theta | \alpha, \beta) \times \text{Gamma}(\lambda | \alpha, \beta) \frac{1}{111} \\ &\propto \left[\prod_{t=1851}^k e^{-\theta} \theta^{y_i} \prod_{t=k+1}^{1962} e^{-\lambda} \lambda^{y_i} \right] \theta^{\alpha-1} e^{-\beta\theta} \lambda^{\alpha-1} e^{-\beta\lambda} \\ &\propto \theta^{\sum_{t=1851}^k y_i + \alpha - 1} e^{-(\beta+k)\theta} \lambda^{\sum_{t=k+1}^{1962} y_i + \alpha - 1} e^{-\beta\lambda} \end{aligned}$$

So, the full conditionals are known, and critically for Gibbs, can easily be sampled from.

$$\theta \sim \text{Gamma} \left(\sum_{t=1851}^k y_i + \alpha, k + \beta \right)$$

$$\lambda \sim \text{Gamma} \left(\sum_{t=k+1}^{1962} y_i + \alpha, 1962 - k + \beta \right)$$

$$p(k | \mathbf{y}, \theta, \lambda, b_1, b_2) = \frac{L(\mathbf{y} | \theta, \lambda, b_1, b_2)}{\sum_{j=1}^n L(\mathbf{y} | \theta, \lambda, b_1, b_2)}$$

where the likelihood is defined as

$$L(\mathbf{y} | \theta, \lambda, b_1, b_2) = e^{(\lambda - \theta)} \left(\frac{\theta}{\lambda} \right)^{\sum_1^k y_i}$$

```
y = data_vector
# Gibbs sampler for the coal mining change point
# initialization
n <- length(y)
#length of the data
m <- 10^4
#length of the chain
mu <- numeric(m)
lambda <- numeric(m)
k <- numeric(m)
L <- numeric(n)
k[1] <- sample(1:n, 1) ## tau
mu[1] <- 1
lambda[1] <- 1
b1 <- 1
b2 <- 1
```

The algorithm explained by Carlin et al is simple. For $t \in \{1, 2, \dots, m\}$

1. Sample $\theta_t \sim \text{Gamma}(a_1 + \sum_1^k y_i, k_{t-1} + b_{1,t-1})$

2. Sample $\lambda_t \sim \text{Gamma}(a_2 + \sum_{k+1}^n y_i, n - k_{t-1} + b_{2,t-1})$
3. Sample $b_1 \sim \text{Gamma}(a_1 + c_1, (\theta_t + d_1))$
4. Sample $b_1 \sim \text{Gamma}(a_2 + c_2, (\lambda_t + d_2))$
5. For $j \in 1, \dots, n$ calculate $L(\mathbf{y}|\theta, \lambda, b_1, b_2)$, from there you'll obtain $p(k|\mathbf{y}, \theta, \lambda, b_1, b_2)$

```
# run the Gibbs sampler
for (i in 2:m){
  kt <- k[i-1]
  #generate mu
  r <- .5 + sum(y[1:kt])
  mu[i] <- rgamma(1, shape = r, rate = kt + b1)
  #generate lambda
  if (kt + 1 > n) r <- .5 + sum(y) else
  r <- .5 + sum(y[(kt+1):n])
  lambda[i] <- rgamma(1, shape = r, rate = n - kt + b2)
  #generate b1 and b2
  b1 <- rgamma(1, shape = .5, rate = mu[i]+1)
  b2 <- rgamma(1, shape = .5, rate = lambda[i]+1)

  for (j in 1:n) {
    L[j] <- exp((lambda[i] - mu[i]) * j) *
      (mu[i] / lambda[i])^sum(y[1:j])
  }

  L <- L / sum(L)
  #generate k from discrete distribution L on 1:n
  k[i] <- sample(1:n, prob=L, size=1)
}
```

```
## set burn in
burn_in <- 1000

j <- k[burn_in:m]

print(mean(k[burn_in:m]))
```

```
## [1] 39.82335
```

```
#[1] 39.935
```

```
print(mean(lambda[burn_in:m]))
```

```
## [1] 0.9406728
```

```
#[1] 0.9341033
```

```
print(mean(mu[burn_in:m]))
```

```
## [1] 3.129247
```

```
#[1] 3.108575
```

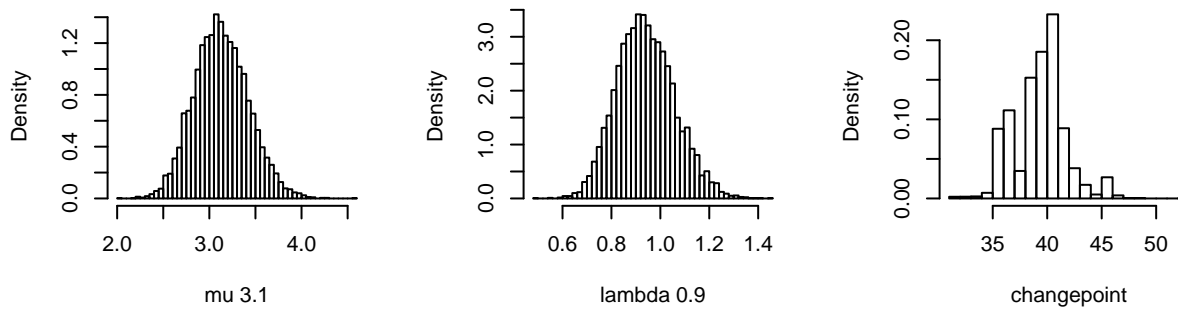
```
## Code for Figure 9.12 on page 276
# histograms from the Gibbs sampler output
par(mfrow=c(2,3))
labelk <- "changepoint"
label1 <- paste("mu", round(mean(mu[burn_in:m]), 1))
label2 <- paste("lambda", round(mean(lambda[burn_in:m]), 1))

hist(mu[burn_in:m], main="", xlab=label1,
     breaks = "scott", prob=TRUE) #mu posterior

hist(lambda[burn_in:m], main="", xlab=label2,
     breaks = "scott", prob=TRUE) #lambda posterior

hist(j, breaks=min(j):max(j), prob=TRUE, main="",
     xlab = labelk)

par(mfcol=c(1,1), ask=FALSE) #restore display
```



```
disasters_array = disasters
```