

Computational Statistics - Lab 04

Annalena Erhard (anner218) and Maximilian Pfundstein (maxpf364)

2019-02-09

Contents

1	Question 1: Computations with Metropolis-Hastings	1
2	Question 2: Gibbs Sampling	9
3	Source Code	15

1 Question 1: Computations with Metropolis-Hastings

Consider the following probability density function:

$$f(x) \propto x^5 e^{-x}, \quad x > 0.$$

You can see that the distribution is known up to some constant of proportionality. If you are interested (**NOT** part of the Lab) this constant can be found by applying integration by parts multiple times and equals 120.

1. Use Metropolis-Hastings algorithm to generate samples from this distribution by using proposal distribution as log-normal $LN(X_t, 1)$, take some starting point. Plot the chain you obtained as a time series plot. What can you guess about the convergence of the chain? If there is a burn-in period, what can be the size of this period?

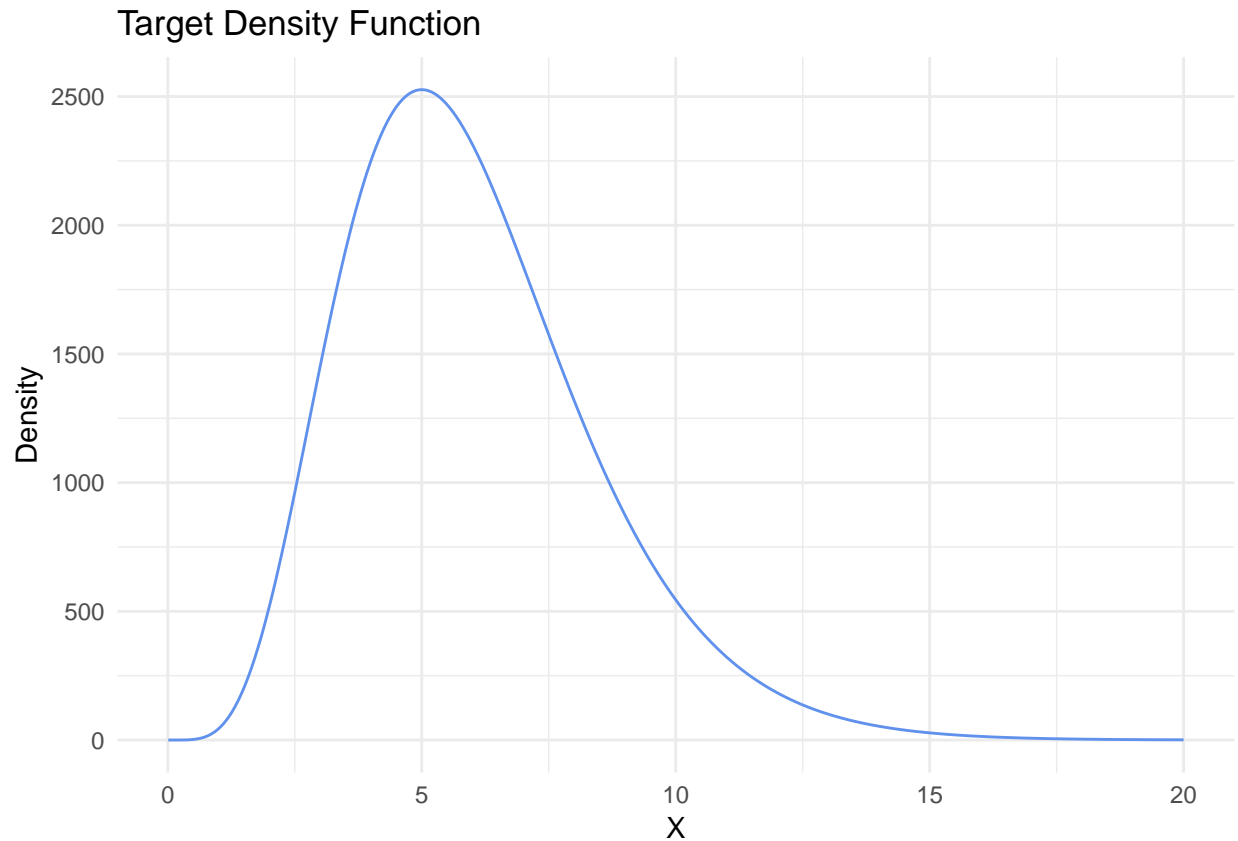
Answer: First we will define the original function with the constant set to get a brief overview how the function actually looks like. We also define the given function without the constant, as we're going to use it later as the target distribution. We use the function without the constant to show that Metropolis-Hastings works without knowing the constant. As random samplings can actually give an x outside of the scope of the function, we will set all values of $x \leq 0$ to a relatively small value.

```
# Target function with original scaling
```

```
f = function(x) {  
  return(120 * x^5 * exp(-x))  
}
```

```
# Target function
```

```
df = function(x) {  
  x = ifelse(x <= 0, 0.000001, x)  
  return(x^5 * exp(-x))  
}
```



The following code chunk defines the Metropolis-Hastings algorithm. The correction factor c is used to handle the asymmetry in the proposal function. The code is commented.

```
## Metropolis Hasting Algorithm
##
## @param n Number of samples from the target distribution.
## @param x_0 Initial state from Pi.
## @param b Burn-in steps to remove from samples.
## @param proposal Selects the proposal function.
## @param keep_burnin Decides if to keep the samples during the burn-in period.
##
## @return Returns a list containing samples.
## @export
##
## @examples
metropolis_hastings = function(n = 1, x_0 = 1, b = 50, proposal = "lnorm",
                               keep_burnin = FALSE) {

  # Vectors to store the samples in
  samples = c()

  # Samples from proposal from the random walk (MC)
  xt = x_0
  xt_1 = x_0

  while (length(samples) < n) {
```

```

# Generate proposal state
if (proposal == "lnorm") {
  x_star = rlnorm(n = 1, meanlog = log(xt), sdlog = 1)

  # Calculate correction factor C
  c = dlnorm(xt_1, meanlog = log(xt), sdlog = 1) /
    dlnorm(x_star, meanlog = log(xt), sdlog = 1)
}
else if (proposal == "chisquared") {
  x_star = rchisq(n = 1, df = floor(xt))

  # Calculate correction factor C
  c = dchisq(x = xt_1, df = floor(xt)) /
    dchisq(x_star, df = floor(xt))
}
else {
  stop("Invalid proposal.")
}

# Calculate acceptance probability alpha
if (df(xt_1) <= 0) {
  # We need this to avoid troublesome areas where the density is so low that
  # it's 0 from a computational point of view.
  alpha = 0
}
else {
  alpha = min(1, df(x_star)/df(xt_1) * c)
}

# Generate u from uniform
u = runif(n = 1, min = 0, max = 1)

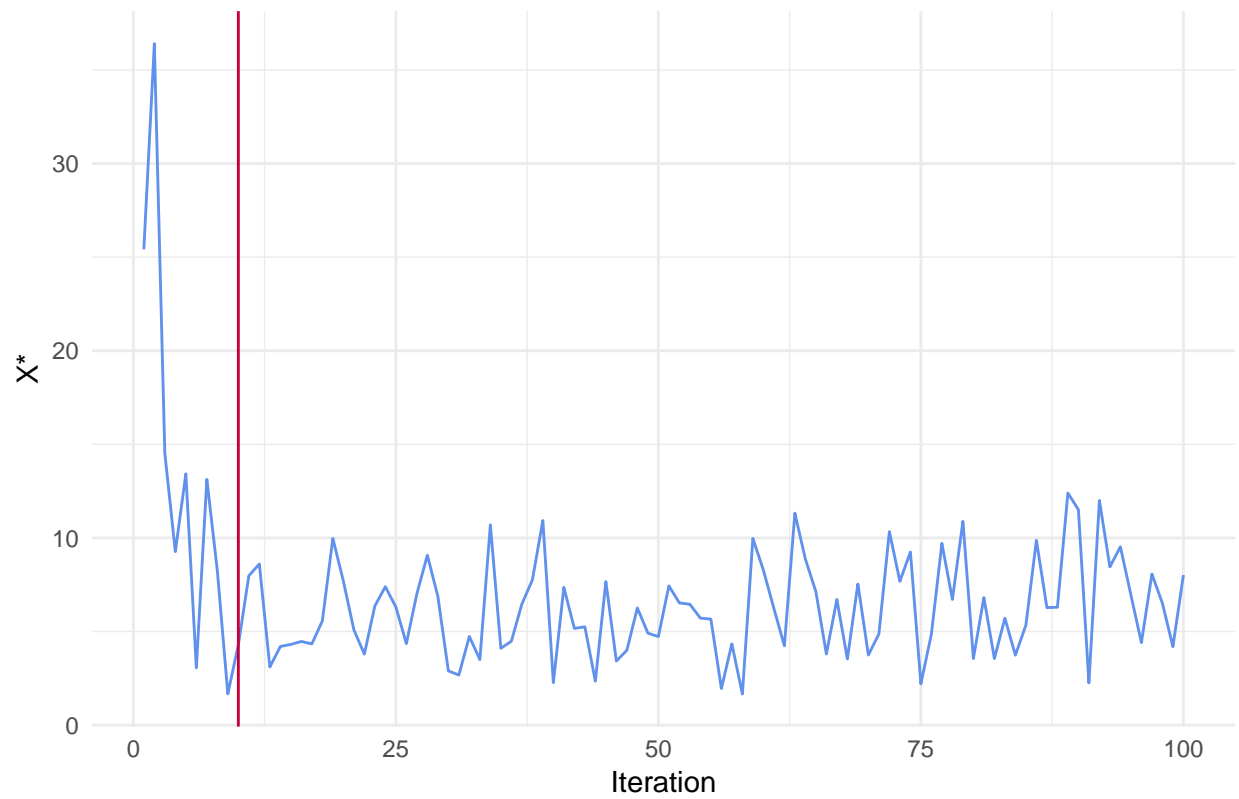
# Decide if to accept or reject the proposal
if (u <= alpha) {
  # Accept
  xt_1 = xt
  xt = x_star
  samples = c(samples, x_star)
}
else {
  # Reject
  xt = xt_1
}
}

# Return samples
if (keep_burnin) return(samples)
return(samples[b+1:length(samples)])
}

```

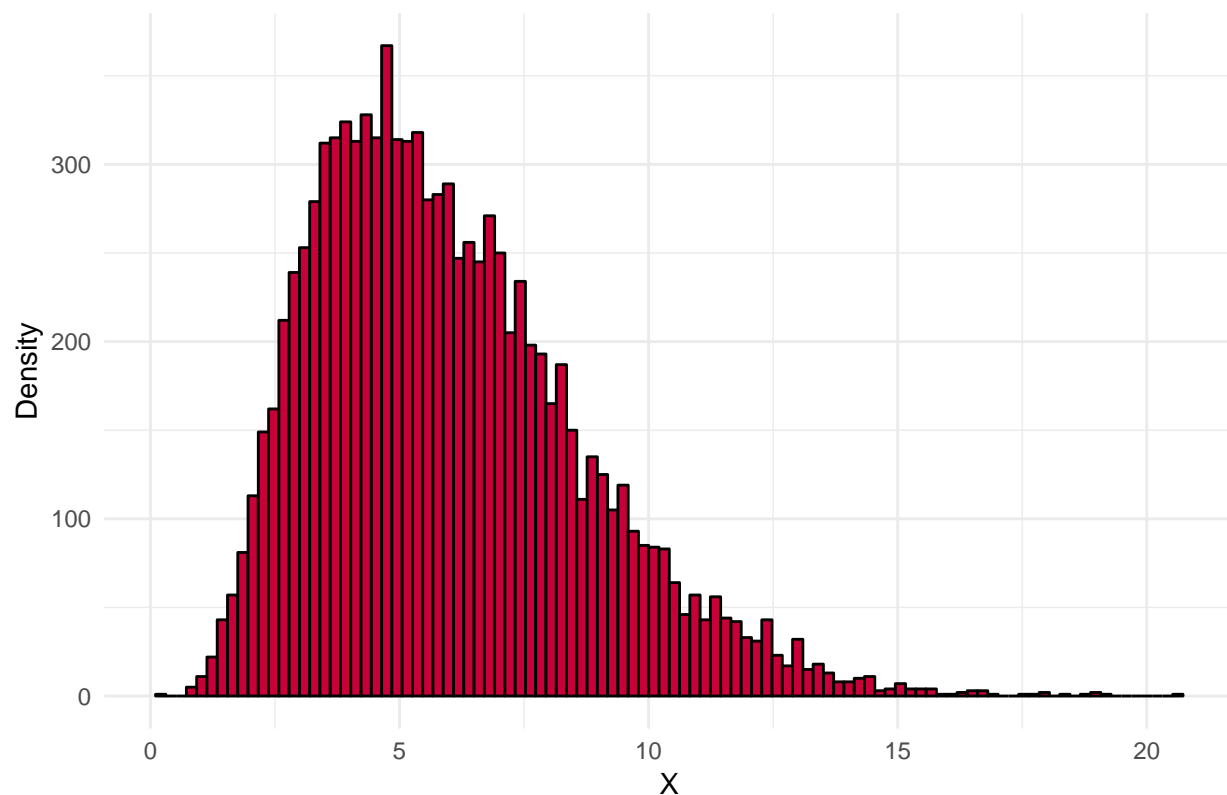
For the lognormal distribution as the proposal we selected a starting point which is far from the converging value to illustrate the burn-in period. We can see that we reach convergence rather quickly after around 8 iterations. We increased the limit to 10 to be sure to get into the area of the converging value.

Traceplot For The Burn-In Period (burnin = 10)



The following plot shows 10.000 samples with $x_0 = 5$ as a starting point and burn-in iterations set to 100.

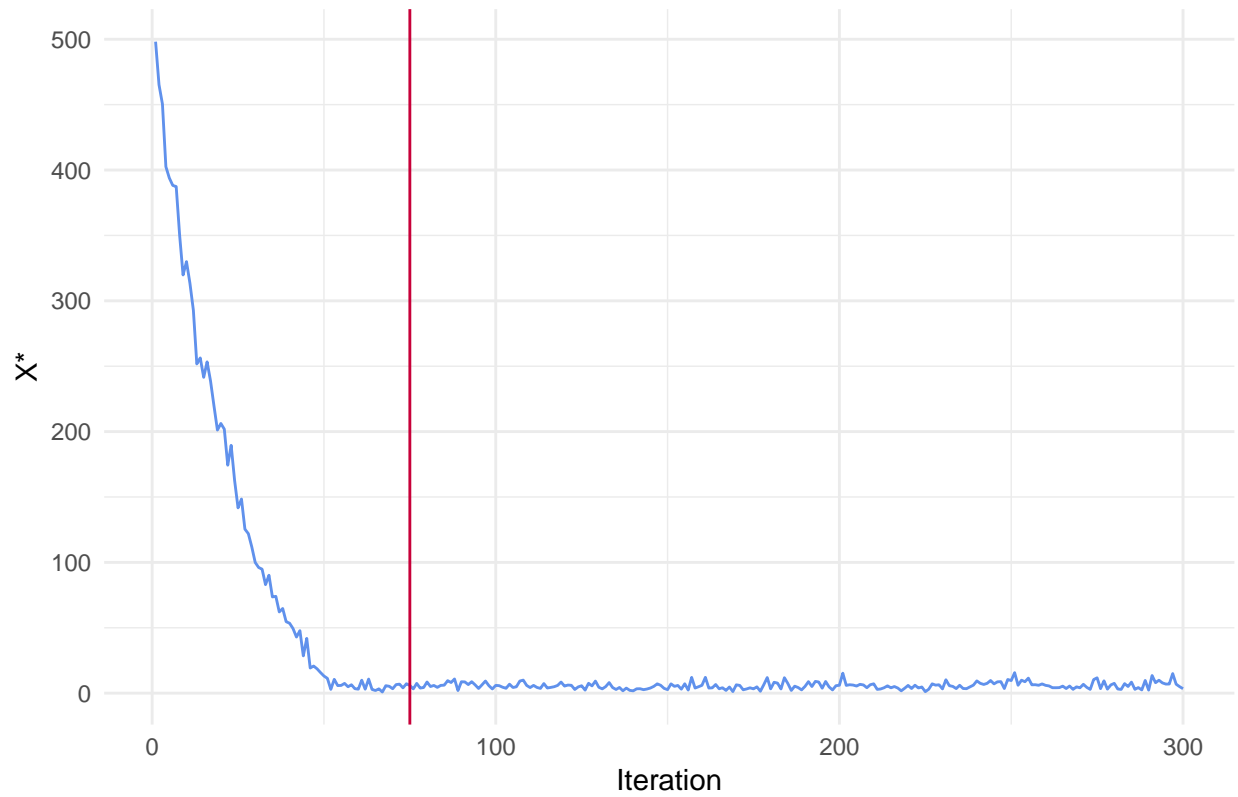
Samples From Target Function Using Normal Proposal



2. Perform Step 1 by using the chi-square distribution $\chi^2(\lfloor X_t + 1 \rfloor)$ as a proposal distribution, where $\lfloor x \rfloor$ is the floor function, meaning the integer part of x for positive x , i.e. $\lfloor 2.95 \rfloor = 2$.

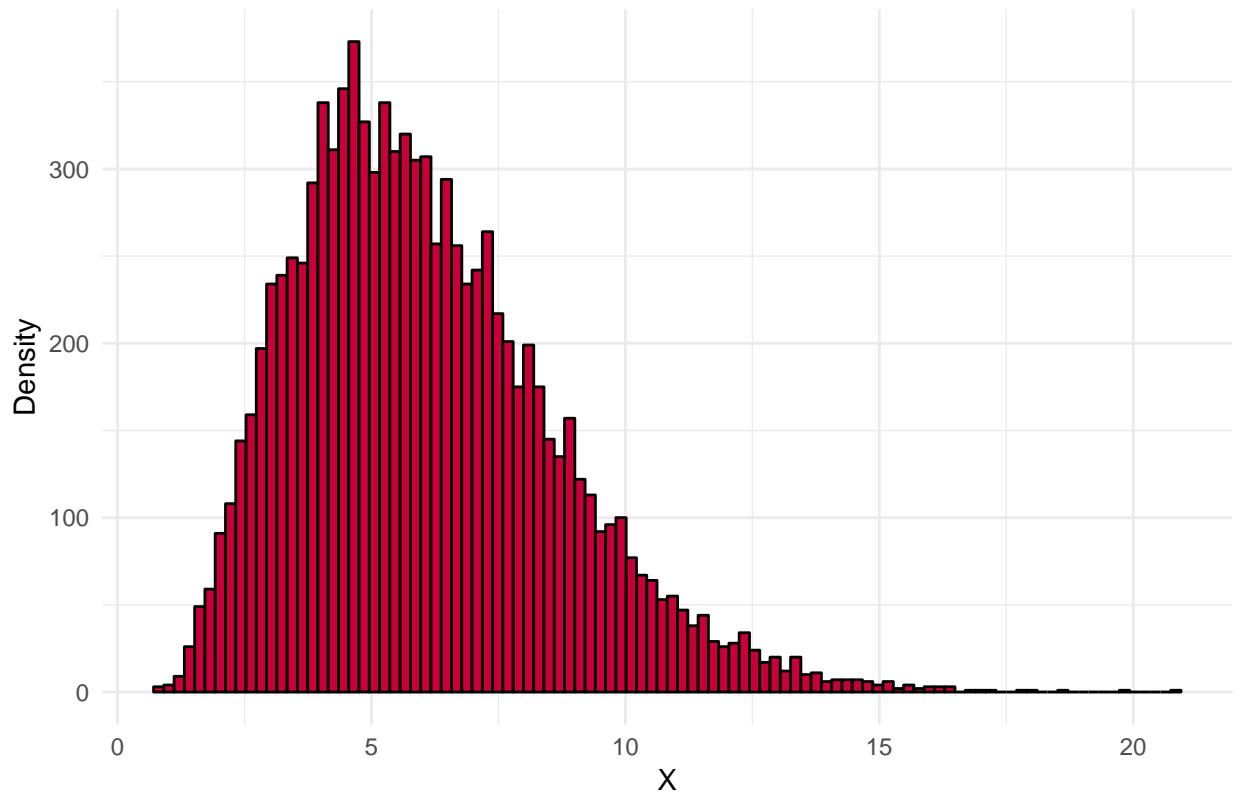
Answer: The trace plot shows the burn-in period for the chi-square distribution. We see that it takes quite longer to achieve convergence. We set the burn-in iterations to 75 to be sure to converge.

Traceplot For The Burn-In Period (burnin = 75)



Again you can see 10.000 samples with $x_0 = 5$ as a starting point and burn-in iterations set to 75.

Samples From Target Function Using Chi-Squared Proposal



3. Compare the results of Steps 1 and 2 and make conclusions.

Answer: The samples seem to actually be taken from the real distribution and in this context it doesn't matter which proposal distribution we take. Comparing the burn-in times we see that it seems to take longer for the chi-squared proposal to converge. We have to keep in mind that this mostly depends on the initial state of the MCMC. It's not so easy to take an initial value which is far of from the converging value as we get densities around 0 which makes it quite difficult to actually calculate c and α . As long as we take an initial state not too far off from a low density, we should be fine, as the algorithm automatically avoids really low density regions.

We assume as long as the proposal distribution mostly covers the target distribution and the initial state is selected quite reasonable (which is not always the case in the “real world”) the Metropolis-Hastings works quite well.

4. Generate 10 MCMC sequences using the generator from Step 2 and starting points 1, 2, ..., or 10. Use the Gelman-Rubin method to analyze convergence of these sequences.

Answer: We can see that the Gelman-Rubin factor is close to 1 with a sequence length of 1000 which indicates that our sequences have converged. The usage of the implementation from the ‘code’ package can be found below.

This self written function is also called with a sequence length of just 5 to demonstrate that the Gelman-Ruben factor increases if the sequence has not converged.

```
gelman_rubin_factor = function(sequence_matrix) {  
  
  k = nrow(sequence_matrix)  
  n = ncol(sequence_matrix)
```

```

B = n/(k-1) * sum((rowMeans(sequence_matrix) - mean(sequence_matrix))^2)
# S_squared = colSums((sequence_matrix - rowMeans(sequence_matrix))^2 / (n - 1))
S_squared = rowSums((sequence_matrix - rowMeans(sequence_matrix))^2 / (n - 1))
W = sum(S_squared / k)
V = ((n - 1) / n * W) + (1/n * B)
R = sqrt(V / W)
return(R)
}

```

```
## [1] 1.000355
```

```
## [1] 1.228422
```

The following output is based three sets of multiple sequences (with starting points 1...10) and used the package coda. The first set of sequences uses 5, the second 10 and the last uses 50 iterations. We can see that the point estimate (at 95% confidence) converges towards 1 with an increasing sequence length which indicates that the set has converged.

The Gelman-Rubin factor works by comparing the variance of the sequences within a set. As more iterations are performed, the MCMC depends less on the starting point until it finally holds no more information about that and the sequences have the same variance compared to themselves and compares to the others. This is when the Gelman-Ruby factor is near 1.

```
## Potential scale reduction factors:
```

```
##
```

```
##      Point est. Upper C.I.
```

```
## [1,]      1.6      3
```

```
## Potential scale reduction factors:
```

```
##
```

```
##      Point est. Upper C.I.
```

```
## [1,]      1.02     1.16
```

```
## Potential scale reduction factors:
```

```
##
```

```
##      Point est. Upper C.I.
```

```
## [1,]      1.04     1.1
```

5. Estimate

$$\int_0^{\infty} xf(x)dx$$

using the samples from Steps 1 and 2.

Answer: To estimate this integral we take our previous samples. We then calculate:

$$\int_0^{\infty} xf(x)dx = E[x] \sim \frac{1}{n} \sum_{i=1}^n x_i$$

where x_i are our samples. As the decomposed left-side function is just x , this is all we have to do. The limits are given by the proposing function.

```

valid_samples_lnorm = results_lnorm[!is.na(results_lnorm)]
sum(valid_samples_lnorm) / length(valid_samples_lnorm)

```

```
## [1] 5.973009
```



```
valid_samples_chisquared = results_chisquared[!is.na(results_chisquared)]
sum(valid_samples_chisquared) / length(valid_samples_chisquared)
```

```
## [1] 6.053069
```

6. The distribution generated is in fact a gamma distribution. Look in the literature and define the actual value of the integral. Compare it with the one you obtained.

Answer: We can see that it is the following Gamma distribution and that the calculated integral is (almost) the same as the one we would expect.

$$\Gamma(6, 1) \Rightarrow E[\Gamma(6, 1)] = 6 * 1 = 6$$

Taking into account that $c = 120$ we can easily calculate the full integral which is:

$$\int_0^{\infty} xf(x)dx = E[\Gamma(6, 1)] * c = 6 * 120 = 720$$

2 Question 2: Gibbs Sampling

concentration of a certain chemical was measured in a water sample, and the result was stored in the data `chemical.RData` having the following variables:

- X : day of the measurement
- Y : measured concentration of the chemical.

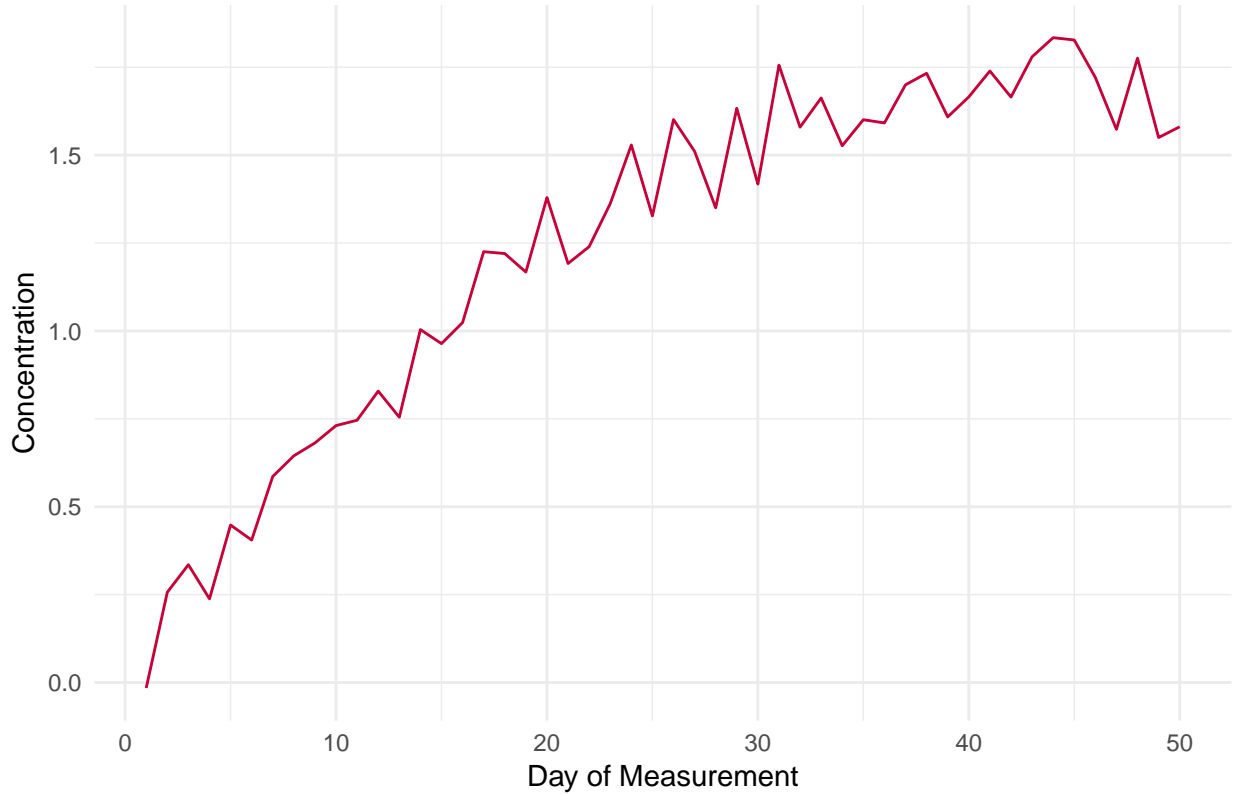
The instrument used to measure the concentration had certain accuracy; this is why the measurements can be treated as noisy. Your purpose is to restore the expected concentration values.

1. Import the data to R and plot the dependence of Y on X . What kind of model is reasonable to use here?

Answer: It looks like that a random walk using a porposal distribution might fit this graph as the starting points seems fo be way of but after a period of time the graph seems to converge and oscillate around the converged value as we have seen in the exercise before.

X	Y
1	-0.0156108
2	0.2568189
3	0.3351229
4	0.2380964
5	0.4480268
6	0.4051863

Dependence from Concentration on Day of Measurement



2. A researcher has decided to use the following (random-walk) Bayesian model (n =number of observations, $\vec{\mu} = (\mu_1, \dots, \mu_n)$ are unknown parameters):

$$Y_i = \mathcal{N}(\mu_i, \text{variance} = 0.2), \quad i = 1, \dots, n$$

where the prior is

$$p(\mu_1) = 1$$

$$p(\mu_{i+1}|\mu_i) = \mathcal{N}(\mu_i, 0.2), i = 1, \dots, n-1.$$

Present the formulae showing the likelihood $p(\vec{Y}|\vec{\mu})$ and the prior $p(\vec{\mu})$. **Hint:** a chain rule can be used here $p(\vec{\mu}) = p(\mu_1)p(\mu_2|\mu_1)p(\mu_3|\mu_2)\dots p(\mu_n|\mu_{n-1})$

Answer: Using the chain rule, we get the formulas for the likelihood and the prior.

The formula for the likelihood is given by:

$$p(\vec{Y}|\vec{\mu}) = \prod_{i=1}^n Y_i = \mathcal{N}(\mu_1|0.2) * \mathcal{N}(\mu_2|0.2) * \dots * \mathcal{N}(\mu_n|0.2)$$

Replacing with the normal distribution it looks like this:

$$p(\vec{Y}|\vec{\mu}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}((\mu_2-\mu_1)^2 + (\mu_3-\mu_2)^2 + \dots + (\mu_n-\mu_{n-1})^2)}$$

We will insert σ at the very end in the coding chunks when we have the marginals for the Gibbs Sampler.
The formula for the prior is given by:

$$p(\vec{\mu}) = 1 * \mathcal{N}(\mu_1|0.2) * \mathcal{N}(\mu_2|0.2) * \dots * \mathcal{N}(\mu_{n-1}|0.2)$$

$$p(\vec{Y}|\vec{\mu}) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}((y_1-\mu_1)^2+(y_2-\mu_2)^2+\dots+(y_{n-1}-\mu_{n-1})^2+y_n-\mu_n)^2}$$

3. Use Bayes' Theorem to get the posterior up to a constant proportionality, and then find out the distributions of $(\mu_i|\vec{\mu}_{-i}, \vec{Y})$, where μ_{-i} is a vector containing all μ values except of μ_i .

Hint A: consider for separate formulae for $(\mu_1|\vec{\mu}_{-1}, \vec{Y})$, $(\mu_n|\vec{\mu}_{-n}, \vec{Y})$ and then a formula for all remaining $(\mu_i|\vec{\mu}_{-i}, \vec{Y})$.

Hint B:

$$e^{-\frac{1}{d}((x-a)^2+(x-b)^2)} \propto e^{-\frac{(x-(a+b)/2)^2}{d/2}}$$

Hint C:

$$e^{-\frac{1}{d}((x-a)^2+(x-b)^2+(x-c)^2)} \propto e^{-\frac{(x-(a+b+c)/3)^2}{d/3}}$$

Bayes Theorem states that:

$$p(\vec{\mu}|\vec{y}) = p(\vec{\mu})p(\vec{y}|\vec{\mu})$$

We will plug in the formulas from above. As we have to find the posterior up to a constant proportionality, we will let the constants disappear in our terms.

$$p(\vec{\mu}|\vec{y}) \propto e^{-\frac{1}{2\sigma^2}((\mu_2-\mu_1)^2+(\mu_3-\mu_2)^2+\dots+(\mu_n-\mu_{n-1})^2)} e^{-\frac{1}{2\sigma^2}((y_1-\mu_1)^2+(y_2-\mu_2)^2+\dots+(y_{n-1}-\mu_{n-1})^2+y_n-\mu_n)^2}$$

We see that every term in the exponent from both es contains the same μ , as indicated by the colors. Using hint B we can summarize it as follows:

$$p(\vec{\mu}|\vec{y}) \propto e^{-\frac{(-\mu_1-\frac{\mu_2+y_1}{2})^2}{\sigma^2}-\frac{(-\mu_2-\frac{\mu_3+y_2}{2})^2}{\sigma^2}-\dots-\frac{(-\mu_{n-1}-\frac{\mu_n+y_{n-1}}{2})^2}{\sigma^2}-\frac{(y_n-\mu_n)^2}{2\sigma^2}}$$

We can see that the last term is different, as it does not have a corresponding partner.

Now we use this posterior to derive the marginals. For getting the marginals we will need to find the terms that are dependant on μ_i .

$$p(\mu_1|\vec{y}) \propto e^{-\frac{(-\mu_1+\frac{\mu_2+y_1}{2})^2}{\sigma^2}}$$

$$p(\mu_2|\vec{y}) \propto e^{-\frac{(-\mu_1+\frac{\mu_2+y_1}{2})^2}{\sigma^2}-\frac{(-\mu_2+\frac{\mu_3+y_2}{2})^2}{\sigma^2}}$$

...

$$p(\mu_{n-1}|\vec{y}) \propto e^{-\frac{\left(-\mu_{n-2} + \frac{\mu_{n-1} + y_{n-2}}{2}\right)^2}{\sigma^2} - \frac{\left(-\mu_{n-1} + \frac{\mu_n + y_{n-1}}{2}\right)^2}{\sigma^2}}$$

As the last term does not have a *partner* (see colors) we cannot combine the terms.

$$p(\mu_n|\vec{y}) \propto e^{-\frac{\left(-\mu_{n-1} + \frac{\mu_n + y_{n-1}}{2}\right)^2}{\sigma^2} - \frac{(y_n - \mu_n)^2}{\sigma^2}}$$

Observing the equations for the marginals we have to distinguish three cases, the first marginal, the last marginal and all other marginals. First we will write each term in the power of \mathbf{e} as a normal distribution, for that we have to adjust some of the terms. After that we have (except for the first marginal) the product of two normal distributions which is a normal distribution again. Let's start with the first marginal, as it's the easiest one.

As we already have the dependant (μ_1) neatly on the left side, we can directly spot the difference to the normal distribution.

$$p(\mu_1|\vec{y}) \propto \mathcal{N}\left(\frac{1}{2}(\mu_2 + y_1), \frac{1}{2}\sigma^2\right)$$

For the next distributions this process will be a bit more cumbersome. We first have to rewrite the fractions in the \mathbf{e} exponent to have the dependant (μ_i) on the left side to spot the normal distribution. As a small recap, this is the formula for the marginals except the first and last one:

$$p(\mu_i|\vec{y}) \propto e^{-\frac{\left(-\mu_{i-1} + \frac{\mu_i + y_{i-1}}{2}\right)^2}{\sigma^2} - \frac{\left(-\mu_i + \frac{\mu_{i+1} + y_i}{2}\right)^2}{\sigma^2}}$$

Adjusting the first fraction in the \mathbf{e} term yields in:

$$p(\mu_i|\vec{y}) \propto e^{-\frac{(\mu_i - (2\mu_{i-1} - y_{i-1}))^2}{4\sigma^2} - \frac{\left(-\mu_i + \frac{\mu_{i+1} + y_i}{2}\right)^2}{\sigma^2}}$$

Now we can rewrite this as a product of two normal distributions:

$$p(\mu_i|\vec{y}) \propto \mathcal{N}(2\mu_{i-1} - y_{i-1}, 2\sigma^2) * \mathcal{N}\left(\frac{1}{2}\mu_i + y_i, \frac{1}{2}\sigma^2\right)$$

The product of two normal distributions is given by (see <https://www.johndcook.com/blog/2012/10/29/product-of-normal-pdfs/> as a recap if not present):

$$\sigma_{new}^2 = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

$$\mu_{new} = \frac{\sigma_1^{-2} \mu_1 + \sigma_2^{-2} \mu_2}{\sigma_1^{-2} + \sigma_2^{-2}}$$

Applying this rule we receive the following normal distribution in the end:

$$\mathcal{N}\left(\frac{1}{5}(2\mu_{i-1} + 2\mu_{i+1} + 2y_i - y_{i-1}), \frac{2}{5}\sigma^2\right)$$

For the last marginal we can reuse the \mathbf{e} term from the previous marginals for the first distribution as only the right part (the second normal distribution) changes.

$$p(\mu_n|\vec{y}) \propto \mathcal{N}(2\mu_{i-1} - y_{i-1}, 2\sigma^2) * \mathcal{N}(y_i, \sigma^2)$$

Now we have to combine those again, by applying the above mentioned rule, thus we receive the following for the last distribution:

$$(\mu_n|\vec{y}) \propto \mathcal{N}\left(\frac{1}{3}(2\mu_{i-1} - y_{i-1} + 2y_i), \frac{2}{3}\sigma^2\right)$$

So finally we have all the desired marginals. It's time for Gibbs Sampling!

4. Use the distributions derived in Step 3 to implement a Gibbs sampler that uses $\vec{\mu}^0 = 0, \dots, 0$ as a starting point. Run the Gibbs sampler to obtain 1000 values of $\vec{\mu}$ and then compute the expected value of $\vec{\mu}$ versus X and Y versus X in the same graph. Does it seem that you have managed to remove the noise? Does it seem that the expected value of $\vec{\mu}$ can catch the true underlying dependence between Y and X?

```
get_mu = function(i, sigma = 0.2, mu, Y) {
  if (i == 1) {
    # First Marginal
    return(rnorm(n = 1, mean = (mu[2] + Y[1])/2, sd = sqrt(1/2 * sigma)))
  }
  else if (i == 50) {
    # Last Marginal
    return(rnorm(n = 1, mean = (2 * mu[i-1] - Y[i-1] + 2 * Y[i])/3,
      sd = sqrt(2/3 * sigma)))
  }

  # General Marginals
  return(rnorm(n = 1, mean = (2 * mu[i-1] + 2 * mu[i+1] + 2 * Y[i] - Y[i-1])/5,
    sd = sqrt(2/5 * sigma)))
}

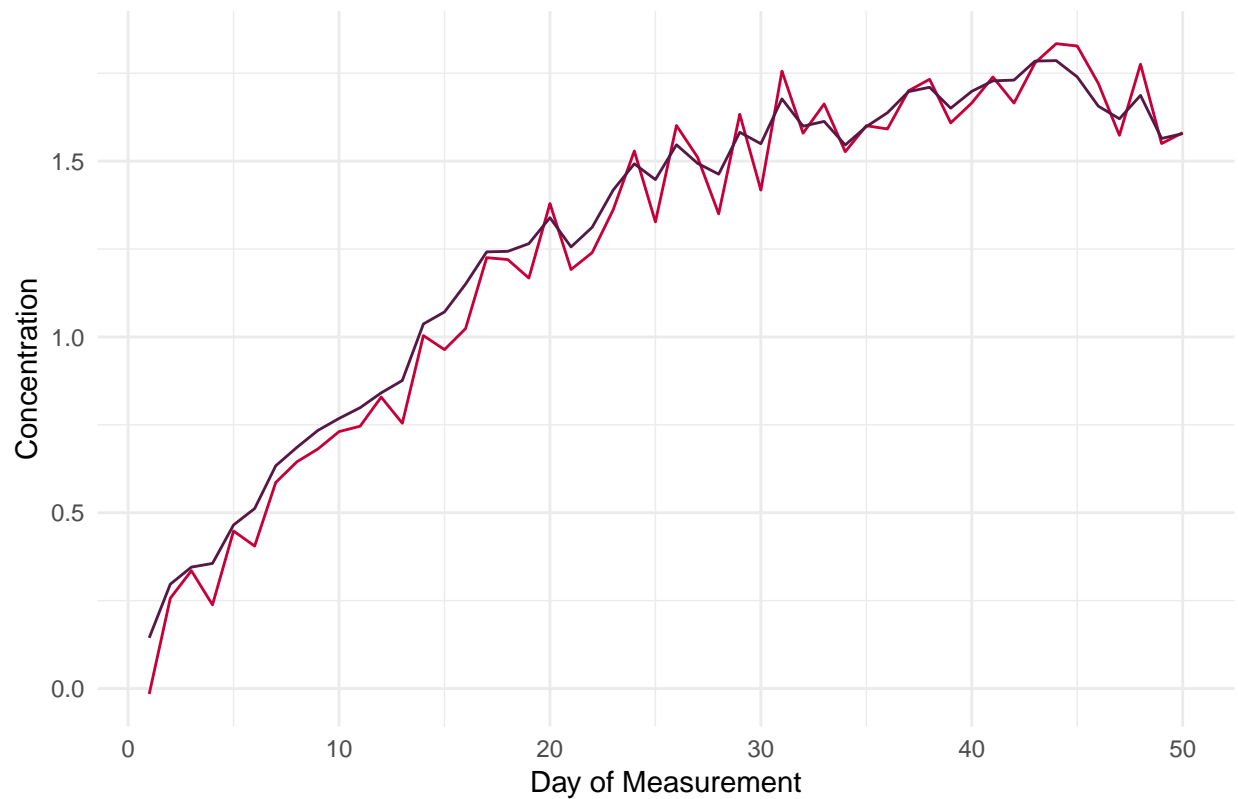
gibbs_sample = function(n, Y, include_matrix = FALSE) {
  # Vectors to store the samples in
  mu_matrix = matrix(0, ncol = length(Y), nrow = n)
  mu = rep(0, length(Y))

  for(j in 1:n) {
    for (i in 1:length(Y)) {
      mu[i] = get_mu(i, sigma = 0.2, mu = mu, Y = Y)
    }
    mu_matrix[j,] = mu
  }

  if (include_matrix) {
    return(list(means = colMeans(mu_matrix), matrix = mu_matrix))
  }

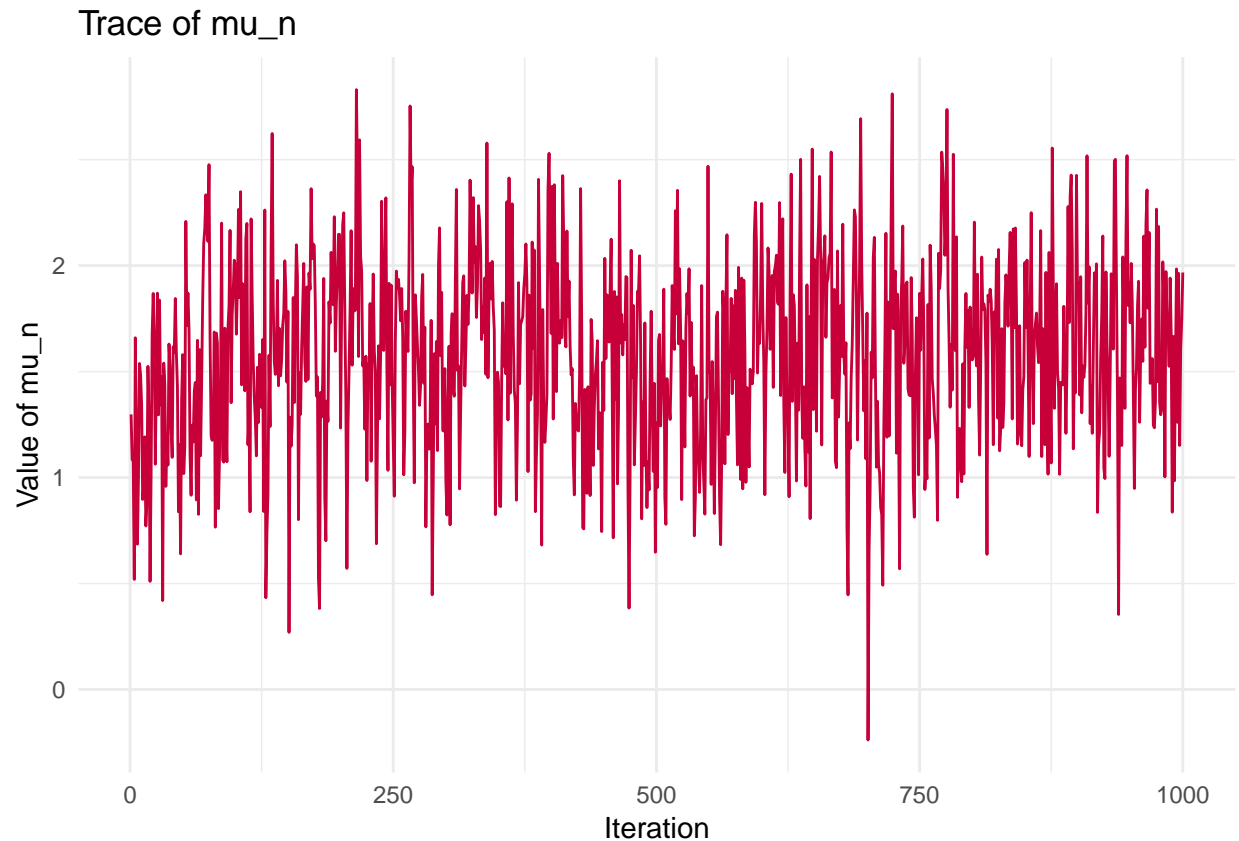
  return(colMeans(mu_matrix))
}
```

Dependence from Concentration on Day of Measurement



Looking at the graph it indeed seems like we were able to reduce the noise. It's hard to say if the expected value of $\bar{\mu}$ is able to catch the true underlying dependence between Y and X, but it looks like, as we have less noise, which is some (distributed) error, that it does.

5. Make a trace plot for μ_n and comment on the burn-in period and convergence.



We see that the burn-in period is rather short (roughly 50 to 100 iterations) and that μ_n has converged after the burn-in. The trace jumps around the mean which is close to 1.5.

3 Source Code

```
knitr::opts_chunk$set(echo = TRUE, cache = FALSE, include = TRUE, eval = TRUE)
library(knitr)
library(readxl)
library(ggplot2)
library(gridExtra)
library(coda)
set.seed(12345)

# Target function with original scaling
f = function(x) {
  return(120 * x^5 * exp(-x))
}

# Target function
df = function(x) {
  x = ifelse(x <= 0, 0.000001, x)
  return(x^5 * exp(-x))
}
```

```

sequence = seq(from = 0.01, to = 20, by = 0.01)

real_f = f(sequence)
plotdf = data.frame(sequence, real_f)

ggplot(plotdf) +
  geom_line(aes(x = sequence, y = real_f), color = "#6091ec") +
  labs(title = "Target Density Function", y = "Density",
       x = "X", color = "Legend") +
  theme_minimal()

#' Metropolis Hasting Algorithm
#'
#' @param n Number of samples from the target distribution.
#' @param x_0 Initial state from  $\pi$ .
#' @param b Burn-in steps to remove from samples.
#' @param proposal Selects the proposal function.
#' @param keep_burnin Decides if to keep the samples during the burn-in period.
#'
#' @return Returns a list containing samples.
#' @export
#'
#' @examples
metropolis_hastings = function(n = 1, x_0 = 1, b = 50, proposal = "lnorm",
                              keep_burnin = FALSE) {

  # Vectors to store the samples in
  samples = c()

  # Samples from proposal from the random walk (MC)
  xt = x_0
  xt_1 = x_0

  while (length(samples) < n) {

    # Generate proposal state
    if (proposal == "lnorm") {
      x_star = rlnorm(n = 1, meanlog = log(xt), sdlog = 1)

      # Calculate correction factor C
      c = dlnorm(xt_1, meanlog = log(xt), sdlog = 1) /
        dlnorm(x_star, meanlog = log(xt), sdlog = 1)
    }
    else if (proposal == "chisquared") {
      x_star = rchisq(n = 1, df = floor(xt))

      # Calculate correction factor C
      c = dchisq(x = xt_1, df = floor(xt)) /
        dchisq(x_star, df = floor(xt))
    }
    else {
      stop("Invalid proposal.")
    }
  }
}

```



```

}

# Calculate acceptance probability alpha
if (df(xt_1) <= 0) {
  # We need this to avoid troublesome areas where the density is so low that
  # it's 0 from a computationally point of view.
  alpha = 0
}
else {
  alpha = min(1, df(x_star)/df(xt_1) * c)
}

# Generate u from uniform
u = runif(n = 1, min = 0, max = 1)

# Decide if to accept or reject the proposal
if (u <= alpha) {
  # Accept
  xt_1 = xt
  xt = x_star
  samples = c(samples, x_star)
}
else {
  # Reject
  xt = xt_1
}
}

# Return samples
if (keep_burnin) return(samples)
return(samples[b+1:length(samples)])
}

burnin = 10

results = metropolis_hastings(100, x_0 = 40, b = burnin, proposal = "lnorm",
                             keep_burnin = TRUE)

plotdf = data.frame(index = 1:length(results), values = results)

ggplot(plotdf) +
  geom_line(aes(x = index, y = values), color = "#6091ec") +
  labs(title = "Traceplot For The Burn-In Period (burnin = 10)", y = "X*",
       x = "Iteration", color = "Legend") +
  geom_vline(xintercept = burnin, color = "#C70039") +
  theme_minimal()

results_lnorm = metropolis_hastings(10000, x_0 = 5, b = 100, proposal = "lnorm")
plotdf = data.frame(results_lnorm)

```

```

ggplot(plotdf) +
  geom_histogram(aes(x = results_lnorm),
                 color = "#000000", fill = "#C70039", bins = length(results_lnorm)/100) +
  labs(title = "Samples From Target Function Using Normal Proposal", y = "Density",
       x = "X", color = "Legend") +
  theme_minimal()

burnin = 75

results = metropolis_hastings(300, x_0 = 500, b = burnin, proposal = "chisquared", keep_burnin = TRUE)

plotdf = data.frame(index = 1:length(results), values = results)

ggplot(plotdf) +
  geom_line(aes(x = index, y = values), color = "#6091ec") +
  labs(title = "Traceplot For The Burn-In Period (burnin = 75)", y = "X*",
       x = "Iteration", color = "Legend") +
  geom_vline(xintercept = burnin, color = "#C70039") +
  theme_minimal()

results_chisquared = metropolis_hastings(10000, x_0 = 5, b = 100, proposal = "chisquared")

plotdf = data.frame(results_chisquared)

ggplot(plotdf) +
  geom_histogram(aes(x = results_chisquared),
                 color = "#000000", fill = "#C70039", bins = length(results_chisquared)/100) +
  labs(title = "Samples From Target Function Using Chi-Squared Proposal", y = "Density",
       x = "X", color = "Legend") +
  theme_minimal()

gelman_rubin_factor = function(sequence_matrix) {

  k = nrow(sequence_matrix)
  n = ncol(sequence_matrix)

  B = n/(k-1) * sum((rowMeans(sequence_matrix) - mean(sequence_matrix))^2)
  # S_squared = colSums((sequence_matrix - rowMeans(sequence_matrix))^2 / (n - 1))
  S_squared = rowSums((sequence_matrix - rowMeans(sequence_matrix))^2 / (n - 1))
  W = sum(S_squared / k)
  V = ((n - 1) / n * W) + (1/n * B)
  R = sqrt(V / W)
  return(R)
}

k = 10 # row
n = 1000 # col

sequence_matrix = matrix(NaN, nrow = k, ncol = n)

```

```

for (i in 1:k) {
  sequence_matrix[i,] = metropolis_hastings(n, x_0 = i, b = 0,
                                           proposal = "chisquared", keep_burnin = TRUE)
}

print(gelman_rubin_factor(sequence_matrix))

k = 10 # row
n = 5 # col

sequence_matrix = matrix(NA, nrow = k, ncol = n)

for (i in 1:k) {
  sequence_matrix[i,] = metropolis_hastings(n, x_0 = i, b = 0,
                                           proposal = "chisquared", keep_burnin = TRUE)
}

print(gelman_rubin_factor(sequence_matrix))

results5 = list()
results10 = list()
results50 = list()
k = 10

for (i in 1:k) {
  results5[[i]] = mcmc(metropolis_hastings(5, x_0 = i, b = 0,
                                           proposal = "chisquared", keep_burnin = TRUE))
}

for (i in 1:k) {
  results10[[i]] = mcmc(metropolis_hastings(10, x_0 = i, b = 0,
                                           proposal = "chisquared", keep_burnin = TRUE))
}

for (i in 1:k) {
  results50[[i]] = mcmc(metropolis_hastings(50, x_0 = i, b = 0,
                                           proposal = "chisquared", keep_burnin = TRUE))
}

mcmc_list5 = mcmc.list(results5)
gelman.diag(mcmc_list5)

mcmc_list10 = mcmc.list(results10)
gelman.diag(mcmc_list10)

mcmc_list50 = mcmc.list(results50)
gelman.diag(mcmc_list50)

valid_samples_lnorm = results_lnorm[!is.na(results_lnorm)]
sum(valid_samples_lnorm) / length(valid_samples_lnorm)

```

```

valid_samples_chisquared = results_chisquared[!is.na(results_chisquared)]
sum(valid_samples_chisquared) / length(valid_samples_chisquared)

# Loading RData
load("chemical.RData")
data = data.frame(X, Y)
kable(head(data))

ggplot(data) +
  geom_line(aes(x = X, y = Y), color = "#c70039") +
  labs(title = "Dependence from Concentration on Day of Measurement", y = "Concentration", x = "Day of
  theme_minimal()

get_mu = function(i, sigma = 0.2, mu, Y) {

  if (i == 1) {
    # First Marginal
    return(rnorm(n = 1, mean = (mu[2] + Y[1])/2, sd = sqrt(1/2 * sigma)))
  }
  else if (i == 50) {
    # Last Marginal
    return(rnorm(n = 1, mean = (2 * mu[i-1] - Y[i-1] + 2 * Y[i])/3,
      sd = sqrt(2/3 * sigma)))
  }

  # General Marginals
  return(rnorm(n = 1, mean = (2 * mu[i-1] + 2 * mu[i+1] + 2 * Y[i] - Y[i-1])/5,
    sd = sqrt(2/5 * sigma)))
}

gibbs_sample = function(n, Y, include_matrix = FALSE) {

  # Vectors to store the samples in
  mu_matrix = matrix(0, ncol = length(Y), nrow = n)
  mu = rep(0, length(Y))

  for(j in 1:n) {
    for (i in 1:length(Y)) {
      mu[i] = get_mu(i, sigma = 0.2, mu = mu, Y = Y)
    }
    mu_matrix[j,] = mu
  }

  if (include_matrix) {
    return(list(means = colMeans(mu_matrix), matrix = mu_matrix))
  }

  return(colMeans(mu_matrix))
}

```

```

gibbs_sample_result = gibbs_sample(1000, Y, TRUE)

data$gibbs_samples = gibbs_sample_result$means

ggplot(data) +
  geom_line(aes(x = X, y = Y), color = "#C70039") +
  geom_line(aes(x = X, y = gibbs_samples), color = "#581845") +
  labs(title = "Dependence from Concentration on Day of Measurement", y = "Concentration", x = "Day of
  theme_minimal()

df = data.frame(
  iteration = seq(from = 1, to = length(gibbs_sample_result$matrix[,50]), by = 1),
  mu_n = gibbs_sample_result$matrix[,50])

ggplot(df) +
  geom_line(aes(x = iteration, y = mu_n), color = "#C70039") +
  labs(title = "Trace of mu_n", y = "Value of mu_n", x = "Iteration",
  color = "Legend") +
  theme_minimal()

```