

# Assignment 4

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## 1 General information

I did not use AI for solving this exercise.

## 2 Bioassay model

### 2.1 (a)

Given the prior distributions for two parameters,  $\alpha$  and  $\beta$ :

$$\alpha \propto N(0, 2^2)$$

$$\beta \propto N(10, 10^2)$$

The known correlation between them is represented as  $\rho$ :

$$\text{corr}(\alpha, \beta) = 0.6$$

The mean of this bivariate normal posterior distribution is:

$$\bar{\mu} = (\mu_{\alpha}, \mu_{\beta}) = (0, 10)$$

The covariance matrix for this posterior distribution is:

$$\Sigma = \begin{pmatrix} \sigma_{\alpha}^2 & \rho \sigma_{\alpha} \sigma_{\beta} \\ \rho \sigma_{\alpha} \sigma_{\beta} & \sigma_{\beta}^2 \end{pmatrix} = \begin{pmatrix} 2^2 & 0.6 \times 2 \times 10 \\ 0.6 \times 2 \times 10 & 10^2 \end{pmatrix} = \begin{pmatrix} 4 & 12 \\ 12 & 100 \end{pmatrix}$$

Therefore, the posterior distribution for these parameters can be expressed as a bivariate normal distribution

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = N \left[ \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \begin{pmatrix} \sigma_{\alpha}^2 & \rho \sigma_{\alpha} \sigma_{\beta} \\ \rho \sigma_{\alpha} \sigma_{\beta} & \sigma_{\beta}^2 \end{pmatrix} \right]$$

```
# Posterior distribution
mean_vector <- c(0,10);
covariance_matrix <- matrix(c(4, 12, 12, 100),2)
joint_posterior <- rmvnorm(4000, mean=mean_vector,
                           sigma=covariance_matrix)
head(joint_posterior)
```

```

      [,1]      [,2]
[1,] -4.01069319  5.134246
[2,] -2.25168379 10.242203
[3,]  0.69110230  1.618235
[4,] -3.12710763  0.353354
[5,] -0.01973444 20.363983
[6,]  1.14800490  1.461065

```

```
print("\nCovariance Matrix:")
```

```
[1] "\nCovariance Matrix:"
```

```
print(covariance_matrix)
```

```

      [,1] [,2]
[1,]    4   12
[2,]   12  100

```

```
print("Mean Vector:")
```

```
[1] "Mean Vector:"
```

```
print(mean_vector)
```

```
[1]  0 10
```

## 2.2 (b)

Loading the library and the data.

```

# Useful functions: quantile()
# and mcse_quantile() (from aaltobda)

data("bioassay_posterior")
# The 4000 draws are now stored in the variable `bioassay_posterior`.
# The below displays the first rows of the data:
head(bioassay_posterior)

```

```

      alpha      beta
1 -0.02050577 10.032841
2  1.21738518  4.504546
3  3.04829407 16.239424
4  1.32272770  4.924268
5  1.36274817 12.880561
6  1.08593225  5.943731

```

```

# Extract alpha and beta samples from bioassay_posterior
alpha_samples <- bioassay_posterior$alpha
beta_samples <- bioassay_posterior$beta

# Calculate the number of samples (S)
S <- length(alpha_samples)

# Calculate mean and variance for alpha and beta samples
mean_alpha <- mean(alpha_samples)
mean_beta <- mean(beta_samples)
var_alpha <- var(alpha_samples)
var_beta <- var(beta_samples)

# Calculate mean Monte Carlo Standard Error (MCSE)
mean_alpha_mcse <- sqrt(var_alpha / S)
mean_beta_mcse <- sqrt(var_beta / S)

# Calculate quantiles for alpha and beta samples
alpha_5 <- quantile(alpha_samples, probs = 0.05)
alpha_95 <- quantile(alpha_samples, probs = 0.95)
beta_5 <- quantile(beta_samples, probs = 0.05)
beta_95 <- quantile(beta_samples, probs = 0.95)

# Calculate MCSE for quantiles
alpha_5_mcse <- mcse_quantile(alpha_samples, prob = 0.05)
alpha_95_mcse <- mcse_quantile(alpha_samples, prob = 0.95)
beta_5_mcse <- mcse_quantile(beta_samples, prob = 0.05)
beta_95_mcse <- mcse_quantile(beta_samples, prob = 0.95)

# Output results
cat(
  "Mean and MCSE:\n",
  paste("Mean alpha MCSE:", mean_alpha_mcse, "\n"),
  paste("Mean alpha:", mean_alpha, "\n"),
  paste("So the true value is between ", mean_alpha - 3*mean_alpha_mcse, " and ",
        mean_alpha + 3*mean_alpha_mcse, "\n"),
  paste("REPORT FOR Mean Alpha: ", round(mean_alpha + 3*mean_alpha_mcse,1) ,
        "\n-----\n"),
  paste("Mean beta MCSE:", mean_beta_mcse, "\n"),
  paste("Mean beta:", mean_beta, "\n"),
  paste("So the true value is between ", mean_beta - 3*mean_beta_mcse, " and ",
        mean_beta + 3*mean_beta_mcse, "\n"),
  paste("REPORT FOR Mean Beta: ", round(mean_beta - 3*mean_beta_mcse,0) ,
        "\n-----\n"),
  "\nAlpha Quantiles and MCSE:\n",
  paste("MCSE for 5% alpha quantile:", alpha_5_mcse, "\n"),
  paste("Quantile 5% alpha:", alpha_5, "\n"),
  paste("So the true value is between ", alpha_5 - 3*alpha_5_mcse, " and ",
        alpha_5 + 3*alpha_5_mcse, "\n"),
  paste("REPORT FOR Quantile 5% alpha: ", round(alpha_5 + 3*alpha_5_mcse, 1) ,
        "\n-----\n"),
  paste("MCSE for 95% alpha quantile:", alpha_95_mcse, "\n"),
  paste("Quantile 95% alpha:", alpha_95, "\n"),

```

```

paste("So the true value is between ", alpha_95 - 3*alpha_95_mcse, " and ",
      alpha_95 + 3*alpha_95_mcse, "\n"),
paste("REPORT FOR Quantile 95% alpha:  ", round(alpha_95 + 3*alpha_95_mcse, 1) ,
      "\n-----\n"),
"\nBeta Quantiles and MCSE:\n",
paste("MCSE for 5% beta quantile:", beta_5_mcse, "\n"),
paste("Quantile 5% beta:", beta_5, "\n"),
paste("So the true value is between ", beta_5 - 3*beta_5_mcse, " and ",
      beta_5 + 3*beta_5_mcse, "\n"),
paste("REPORT FOR Quantile 5% beta:  ", round(beta_5 + 3*beta_5_mcse, 1) ,
      "\n-----\n"),
paste("MCSE for 95% beta quantile:", beta_95_mcse, "\n"),
paste("Quantile 95% beta:", beta_95, "\n"),
paste("So the true value is between ", beta_95 - 3*beta_95_mcse, " and ",
      beta_95 + 3*beta_95_mcse, "\n"),
paste("REPORT FOR Quantile 95% beta:  ", round(beta_95 + 3*beta_95_mcse, 0) ,
      "\n-----\n")
)

```

#### Mean and MCSE:

```

Mean alpha MCSE: 0.0148243453551196
Mean alpha: 0.985226289184767
So the true value is between  0.940753253119408  and  1.02969932525013
REPORT FOR Mean Alpha:   1

```

-----

```

Mean beta MCSE: 0.0756001627482693
Mean beta: 10.5964812910431
So the true value is between  10.3696808027983  and  10.823281779288
REPORT FOR Mean Beta:   10

```

-----

#### Alpha Quantiles and MCSE:

```

MCSE for 5% alpha quantile: 0.0260041159750117
Quantile 5% alpha: -0.467591355167553
So the true value is between  -0.545603703092588  and  -0.389579007242518
REPORT FOR Quantile 5% alpha:   -0.4

```

-----

```

MCSE for 95% alpha quantile: 0.0420634167918579
Quantile 95% alpha: 2.61020281115318
So the true value is between  2.48401256077761  and  2.73639306152875
REPORT FOR Quantile 95% alpha:   2.7

```

-----

#### Beta Quantiles and MCSE:

```

MCSE for 5% beta quantile: 0.0704312509185216
Quantile 5% beta: 3.99140320865043
So the true value is between  3.78010945589487  and  4.202696961406
REPORT FOR Quantile 5% beta:   4.2

```

-----

```

MCSE for 95% beta quantile: 0.241212887707373
Quantile 95% beta: 19.3403654436304
So the true value is between  18.6167267805082  and  20.0640041067525
REPORT FOR Quantile 95% beta:   20

```

## 3 Importance sampling

### 3.1 (c)

```
-----

# Useful functions: bioassaylp (from aaltobda)
alpha_test = c(1.896, -3.6, 0.374, 0.964, -3.123, -1.581)
beta_test = c(24.76, 20.04, 6.15, 18.65, 8.16, 17.4)

data("bioassay")

log_importance_weights <- function(alpha, beta) {
  # Do computation here, and return as below.
  # This is the correct return value for the test data provided above.
  weights_array <- numeric(length(alpha))
  weights_array <- bioassaylp(alpha,
                              beta,
                              bioassay$x,
                              bioassay$y,
                              bioassay$n)

  return(c(weights_array))
}
```

### 3.2 (d)

```
normalized_importance_weights <- function(alpha, beta) {
  # Do computation here, and return as below.
  # This is the correct return value for the test data provided above.
  # Calculate weights_array_norm
  weights_array <- exp(log_importance_weights(alpha, beta))

  sum_weights <- sum(weights_array)

  weights_array_norm_final <- weights_array / sum_weights

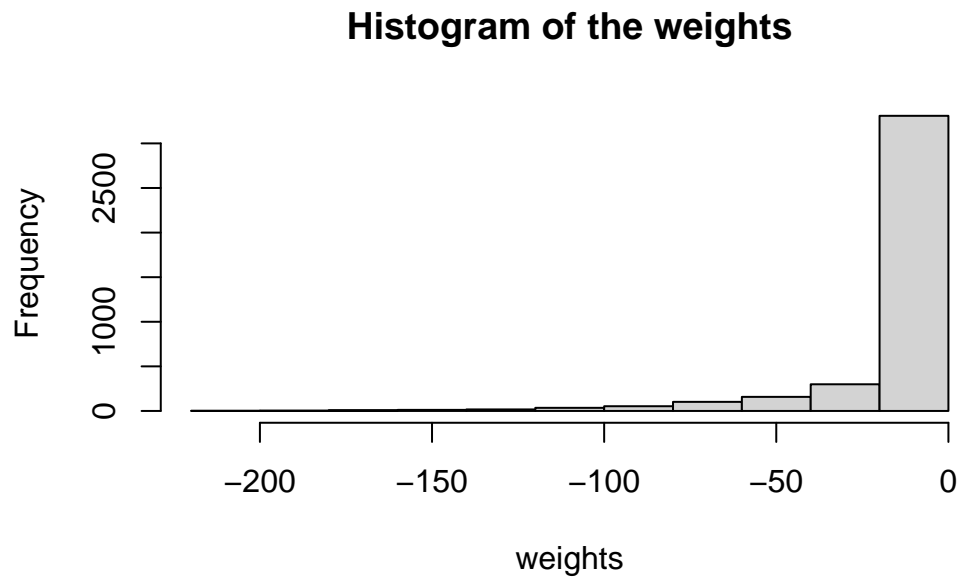
  weights_norm <- c(weights_array_norm_final)

  return(weights_norm)
}
```

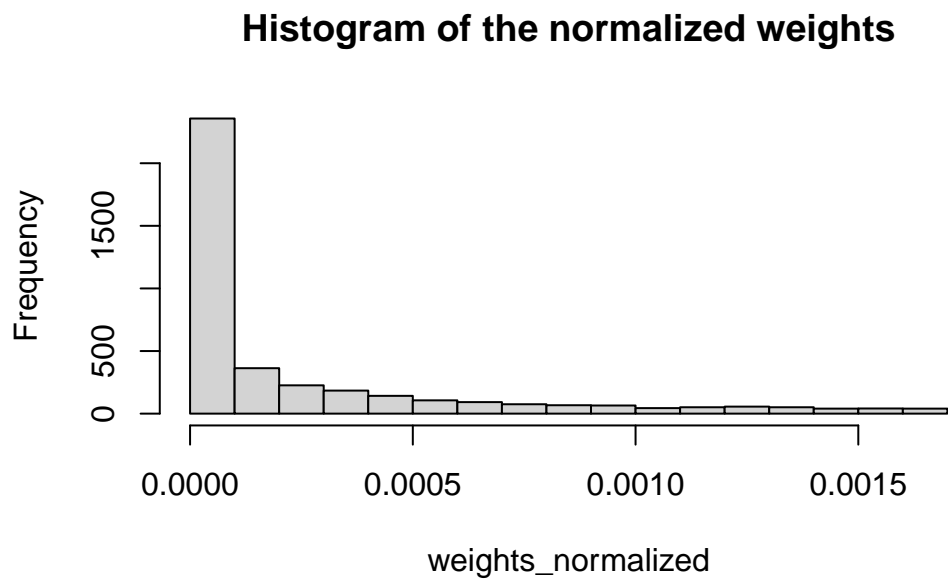
### 3.3 (e)

```
n <- 4000
joint_posterior <- rmvnorm(n, mean = mean_vector,
                           sigma = covariance_matrix)
alpha_samples <- (joint_posterior[,1])
beta_samples <- (joint_posterior[,2])
```

```
weights <- log_importance_weights(alpha_samples, beta_samples)
weights_normalized <- normalized_importance_weights(alpha = alpha_samples, beta = beta_samples)
hist(weights, main = "Histogram of the weights")
```



```
hist(weights_normalized, main = "Histogram of the normalized weights")
```



```
head(weights_normalized)
```

```
[1] 6.226186e-08 1.336182e-03 1.237930e-04 1.190256e-03 2.495296e-24
[6] 4.534852e-04
```

### 3.4 (f)

```
S_eff <- function(alpha, beta) {  
  # Do computation here, and return as below.  
  # This is the correct return value for the test data provided above.  
  weights_normalized <- normalized_importance_weights(alpha, beta)  
  seff <- 1 / sum(weights_normalized^2)  
  return(seff)  
}  
  
s_eff <- S_eff(alpha = alpha_samples, beta = beta_samples)  
  
cat("S_eff: ", s_eff, "\n")
```

```
S_eff: 1130.352
```

### 3.5 (g)

In the context of importance sampling, the effective sample size serves as a measure of how efficiently a set of samples represents the target distribution. A high effective sample size is desirable because it indicates that the samples are making a substantial contribution to the estimation process. Conversely, a low effective sample size suggests that many samples are redundant or don't significantly impact the final result.

Upon examining the histogram, it becomes evident that a substantial number of small weights occur quite frequently. Specifically, weights falling in the range between 0 and 0.0002 appear around 3000 times. However, our goal is to ensure that all samples carry equal importance. Consequently, the effective sample size should ideally be around  $4000 - 3000 = 1000$ , which aligns closely with the calculated value of  $S_{\text{eff}}$ . This adjustment aims to balance the importance of each sample in the estimation process.

### 3.6 (h)

```
posterior_mean <- function(alpha, beta) {  
  # Do computation here, and return as below.  
  # This is the correct return value for the test data provided above.  
  weights_normalized <- normalized_importance_weights(alpha = alpha, beta = beta)  
  alpha_posterior_mean <- 0  
  beta_posterior_mean <- 0  
  for (i in 1:length(alpha)){  
    i  
    alpha_posterior_mean <- alpha_posterior_mean + alpha[i]*weights_normalized[i]  
    beta_posterior_mean <- beta_posterior_mean + beta[i]*weights_normalized[i]  
  }  
  return(c(alpha_posterior_mean, beta_posterior_mean))  
}  
  
posterior_means <- posterior_mean(alpha=alpha_samples, beta=beta_samples)  
  
print("Posterior Means: ")
```

```
[1] "Posterior Means: "
```

```
print(posterior_means)
```

```
[1] 0.9525009 10.4930082
```

```
weight = normalized_importance_weights(alpha_samples, beta_samples)
```

```
alpha_f = (alpha_samples^2) * weight
```

```
beta_f = (beta_samples^2) * weight
```

```
sq_alpha = sum(alpha_f)
```

```
sq_beta = sum(beta_f)
```

```
mean_alpha = posterior_mean(alpha_samples, beta_samples)[1]
```

```
mean_beta = posterior_mean(alpha_samples, beta_samples) [2]
```

```
var_alpha = sq_alpha - (mean_alpha^2)
```

```
var_beta = sq_beta - (mean_beta^2)
```

```
seff = S_eff (alpha_samples, beta_samples)
```

```
mcse_alpha = sqrt(var_alpha/seff)
```

```
mcse_beta = sqrt(var_beta/seff)
```

```
cat ("MCSE alpha", mcse_alpha, "\n")
```

```
MCSE alpha 0.02736892
```

```
cat ("MCSE beta", mcse_beta, "\n")
```

```
MCSE beta 0.1399351
```

```
cat(  
  paste("Mean alpha:", mean_alpha, "\n"),  
  paste("So the true value is between ", mean_alpha - 3*mcse_alpha, " and ",  
        mean_alpha + 3*mcse_alpha, "\n"),  
  paste("REPORT FOR Mean Alpha: ", round(mean_alpha + 3*mcse_alpha, 1) ,  
        "\n-----\n"),  
  paste("Mean beta MCSE:", mean_beta_mcse, "\n"),  
  paste("Mean beta:", mean_beta, "\n"),  
  paste("So the true value is between ", mean_beta - 3*mcse_beta, " and ",  
        mean_beta + 3*mcse_beta, "\n"),  
  paste("REPORT FOR Mean Beta: ", round(mean_beta + 3*mcse_beta, 0) ,  
        "\n-----\n")  
)
```

```
Mean alpha: 0.95250091924671
```

```
So the true value is between 0.870394149325556 and 1.03460768916786
```

```
REPORT FOR Mean Alpha: 1
```

```
-----
```



Mean beta MCSE: 0.0756001627482693

Mean beta: 10.4930081585717

So the true value is between 10.0732028041719 and 10.9128135129716

REPORT FOR Mean Beta: 11

-----