

# Principles of statistical inference project - Part 1

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## 1 Question 1

**Consider a random variable  $X$  that follows an exponential distribution with scale parameter  $\lambda$ .**

The **Exponential Distribution** is a continuous probability distribution that represents the time intervals between consecutive events in a Poisson process, where events happen independently and at a constant average rate. It is defined by a single parameter,  $\lambda$ , referred to as the rate parameter.

### 1.1 Give reference to a publication in which the exponential distribution has been used in practise. Explain the context in which this distribution has been used in this publication.

Mahmud et al. presented a study where they analysed and estimated response times to questions on Twitter [1]. The authors developed predictive models to estimate response wait times, exploring three different approaches:

- **Personalized wait time models:** These models estimate the wait time for a specific user based on their individual history of response wait times. They assume each response event for a user occurs continuously and independently at a constant average rate, modelled by an exponential distribution. Each user's rate parameter  $\lambda$  is estimated as the inverse of their average past response wait times.

These models demonstrated a promising ability to estimate response times on Twitter. They generally outperformed generalized models and showed reasonable accuracy, especially for an hour or more time limits. The choice of cut-off probability (a threshold used to determine whether a user is considered sufficiently likely to respond to a question on Twitter within a given period) significantly influenced the precision and recall of the predictions.

- **Generalized wait time models:** Instead of individual models, a single model is built using the previous responses of all users in the dataset, again using the exponential distribution. The rate parameter  $\lambda$  is estimated from

the responses of all users. This model underperformed compared to the personalized models in estimating response times on Twitter.

- Time-sensitive wait time models: These models incorporate sensitivity to the time of day or day of the week when questions are sent for both generalized and personalized models by calculating the rate parameter based on responses to questions sent during a specific day or hour. Personalized time-sensitive models only considered users with at least five responses during the modelled time interval. Incorporating time sensitivity had a modest positive impact on the generalized models but did not consistently improve the performance of the personalized models.

## 1.2 State the mean and the variance of $X$ .

As  $X$  follows an exponential distribution with scale parameter,  $X \sim \text{Exp}(X)$ , the expected value or mean is:

$$\mathbb{E}[X] = \frac{1}{\lambda} \quad (1)$$

and the variance is:

$$\text{Var}(X) = \frac{1}{\lambda^2} \quad (2)$$

## 1.3 Derive the moment estimator of $\lambda$ .

The p.d.f. for an exponential distribution is:

$$f(x) = \lambda e^{-\lambda x}, x \geq 0, \lambda > 0 \quad (3)$$

The first moment, or expected value:

$$\begin{aligned} \mathbb{E}[X] &= \int_0^{\infty} x f(x) dx \\ &= \int_0^{\infty} x \lambda e^{-\lambda x} dx \\ &= \lambda \int_0^{\infty} x e^{-\lambda x} dx \end{aligned}$$

Integrating by parts, we let:

$$\begin{aligned} u &= x & du &= (1)dx \\ v &= -\frac{e^{-\lambda x}}{\lambda} & dv &= e^{-\lambda x} dx \end{aligned}$$

As  $\int u dv = uv - \int v du$ :

$$\begin{aligned}\mathbb{E}[X] &= \lambda \left( \left[ -\frac{xe^{-\lambda x}}{\lambda} \right]_0^\infty - \int_0^\infty -\frac{e^{-\lambda x}}{\lambda} (1) dx \right) \\ &= \left[ -xe^{-\lambda x} \right]_0^\infty + \int_0^\infty -e^{-\lambda x} dx\end{aligned}$$

Let us consider  $\left[ xe^{-\lambda x} \right]_0^\infty$ :

- $-xe^{-\lambda x} = 0$ , when  $x = 0$
- $\lim_{x \rightarrow \infty} xe^{-\lambda x} = 0$ , as exponential decay dominates polynomial growth

So the first term is removed;

$$\begin{aligned}\mathbb{E}[X] &= \int_0^\infty -e^{-\lambda x} dx \\ &= \left[ -\frac{1}{\lambda} - e^{-\lambda x} \right]_0^\infty \\ &= 0 - \left( -\frac{1}{\lambda} \right) \\ &= \frac{1}{\lambda}\end{aligned}$$

As in the method of moments the sample mean is equal to theoretical expectation;

$$\mathbb{E}[X] = \frac{1}{\lambda} = \overline{X}$$

and solving for  $\lambda$

$$\hat{\lambda} = \frac{1}{\overline{X}} \quad (4)$$

#### 1.4 Use the second moment to obtain another estimator of $\lambda$

For an exponential distribution with rate parameter  $\lambda$ , the second moment,

$$\begin{aligned}\mathbb{E}[X^2] &= \int_0^\infty x^2 f(x) dx \\ &= \int_0^\infty x^2 \lambda e^{-\lambda x} dx \\ &= \lambda \int_0^\infty x^2 e^{-\lambda x} dx\end{aligned}$$

We let:

$$\begin{aligned} u &= x^2 & du &= 2x dx \\ v &= -\frac{e^{-\lambda x}}{\lambda} & dv &= e^{-\lambda x} dx \end{aligned}$$

$$\begin{aligned} \mathbb{E}[X^2] &= \lambda \left( \left[ -\frac{x^2 e^{-\lambda x}}{\lambda} \right]_0^\infty - \int_0^\infty -\frac{e^{-\lambda x}}{\lambda} 2x dx \right) \\ &= \left[ -x^2 e^{-\lambda x} \right]_0^\infty + \int_0^\infty 2x e^{-\lambda x} dx \end{aligned}$$

Let us consider  $\left[ x^2 e^{-\lambda x} \right]_0^\infty$ :

- $-x^2 e^{-\lambda x} = 0$ , when  $x = 0$
- $\lim_{x \rightarrow \infty} x^2 e^{-\lambda x} = 0$ , as exponential decay dominates polynomial growth

Then

$$\mathbb{E}[X^2] = \int_0^\infty 2x e^{-\lambda x} dx$$

We let:

$$\begin{aligned} u &= x & du &= dx \\ v &= -\frac{e^{-\lambda x}}{\lambda} & dv &= e^{-\lambda x} dx \end{aligned}$$

$$\mathbb{E}[X^2] = 2 \left( \left[ -\frac{x e^{-\lambda x}}{\lambda} \right] - \int_0^\infty e^{-\lambda x} dx \right)$$

We have seen previously that the first term will equate to zero.

$$\begin{aligned} \mathbb{E}[X^2] &= 2 \int_0^\infty \frac{e^{-\lambda x}}{\lambda} dx \\ &= \left[ -\frac{2e^{-\lambda x}}{\lambda^2} \right]_0^\infty \\ &= 0 - \left( -\frac{2}{\lambda^2} \right) \\ &= \frac{2}{\lambda^2} \end{aligned}$$

The variance of the exponential distribution is given by:

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\ &= \frac{2}{\lambda^2} - \left( \frac{1}{\lambda} \right)^2 \\ &= \frac{1}{\lambda^2} \end{aligned}$$

We can estimate the sample variance

$$\hat{\sigma}^2 = \frac{1}{\hat{\lambda}^2}$$

and solving for  $\lambda$

$$\hat{\lambda} = \frac{1}{\sqrt{\hat{\sigma}^2}} \quad (5)$$

**1.5 Comment on the unbiasedness and consistency of the moment estimator for  $\lambda$  derived in Q1iii. State any assumption/s that need to be made to check for unbiasedness and consistency.**

The moment estimator  $\hat{\lambda}$  is both unbiased and consistent.

**Unbiasedness:** The estimator  $\hat{\lambda}$  is unbiased if its expectation equals the true parameter  $\lambda$ :

$$\mathbb{E}[\hat{\lambda}] = E\left[\frac{1}{\bar{X}}\right] = \lambda. \quad (6)$$

Since the expectation of the sample mean  $\bar{X}$  for an exponential distribution satisfies  $\mathbb{E}[\bar{X}] = \frac{1}{\lambda}$ , applying Jensen's inequality confirms that the moment estimator is unbiased.

**Consistency:** The estimator  $\hat{\lambda}$  is consistent if its variance decreases to zero as  $n \rightarrow \infty$ . The variance of  $\hat{\lambda}$  is given by:

$$\text{Var}(\hat{\lambda}) = \frac{\lambda^2}{n}. \quad (7)$$

Since  $\frac{\lambda^2}{n} \rightarrow 0$  as  $n \rightarrow \infty$ , it follows that  $\hat{\lambda}$  is a consistent estimator of  $\lambda$ .

**1.6 Use R software to generate 1000 data points from an exponential distributed random variable using any admissible parameter value for  $\lambda$**

The R script generates 1000 points from an exponentially distributed random variable with a rate parameter  $\lambda$  of 1.5. It then plots a histogram of these points and overlays the theoretical density function of the exponential distribution. The result is shown in Figure 1.

```

1 library(ggplot2)
2 library(glue)
3
4 set.seed(50)
5 lambda <- 1.5
6 x <- rexp(n = 1000, rate = lambda)
7
8 data <- data.frame(x = x)
9
10 p <- ggplot(data,
11             aes(x = x)) +
12     geom_histogram(
13         aes(y = after_stat(density)),
14         bins = 50, fill = "blue",
15         color = "black",
16         alpha = 0.6) +
17     stat_function(
18         fun = function(x) lambda * exp(-lambda * x),
19         color = "red",
20         size = 1) +
21     labs(title = glue("Histogram of exponentially distributed
22 random variable with lambda = {lambda}"),
23          x = "x", y = "Density") +
24     theme_minimal() +
25     theme(plot.title = element_text(hjust = 0.5))

```

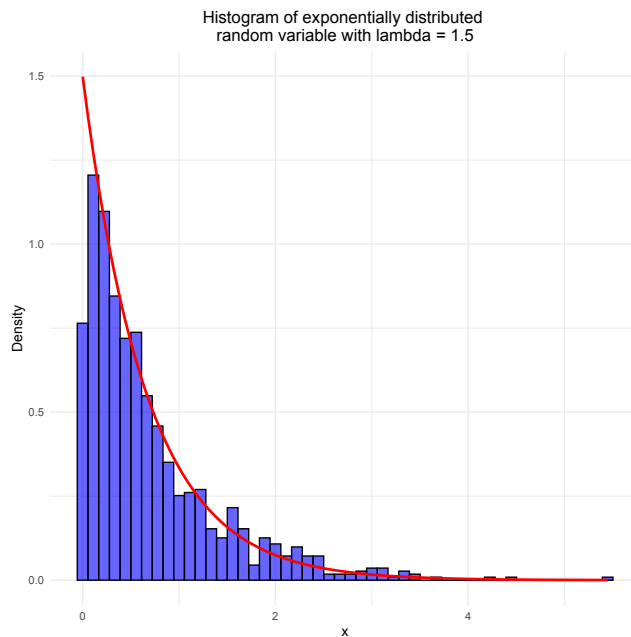


Figure 1: Exponential distributed random variable; histogram of 1000 generated points and theoretical distribution

**1.6.1 Write down the log-likelihood function for this exponentially distributed random variable.**

For sample  $\mathbf{x} = (x_1, \dots, x_n)^T$  obtained on an exponential distributed random variable  $X$ , with parameter vector  $\theta = (\lambda)$ , the likelihood

$$\begin{aligned} L(\mathbf{x}, \theta) &= \prod_{i=1}^n f(x_i, \theta) \\ &= \prod_{i=1}^n \lambda e^{-\lambda x_i} \\ &= \lambda^n e^{-\sum_{i=1}^n \lambda x_i} \end{aligned}$$

The log-likelihood is then

$$l(\mathbf{x}, \theta) = n \log(\lambda) - \lambda \sum_{i=1}^n x_i$$

Taking the derivative with respect to  $\lambda$ ,

$$\frac{\partial l(\mathbf{x}, \theta)}{\partial \lambda} = \frac{n}{\lambda} - \sum_{i=1}^n x_i$$

for maximum  $\frac{\partial l(\mathbf{x}, \theta)}{\partial \lambda}$

$$\begin{aligned} L \frac{\partial l(\mathbf{x}, \theta)}{\partial \lambda} &= 0 \\ \frac{n}{\lambda} - \sum_{i=1}^n x_i &= 0 \\ \frac{n}{\lambda} &= \sum_{i=1}^n x_i \end{aligned}$$

So that

$$\hat{\lambda} = \frac{n}{\sum_{i=1}^n x_i} = \frac{1}{\bar{x}} \quad (8)$$

**1.6.2 Evaluate the log-likelihood function for the generated data as a function of  $\lambda$ , and plot the resulting log-likelihood function against different values of  $\lambda$ . Present the plot together with the answers.**

The following listing calculates and plots the log-likelihood values for an exponential distribution with varying  $\lambda$  values. The resulting plot can be examined in Figure 2

```

1 lambda_values <- seq(0.1, 5, by = 0.01)
2 log_likelihood_values <- sapply(lambda_values,
3 function(lambda) LL_exponential(lambda, x))
4
5 df <- data.frame(lambda_values, log_likelihood_values)
6
7 p <- ggplot(df,
8   aes(x = lambda_values,
9     y = log_likelihood_values)) +
10 geom_point(
11   color = "blue",
12   alpha = 0.6) +
13   labs(
14     title = "Log-Likelihood with varying
15     lambda values",
16     x = "Lambda",
17     y = "Log-Likelihood") +
18   theme_bw()
19
20 quartz()
21 print(p)

```

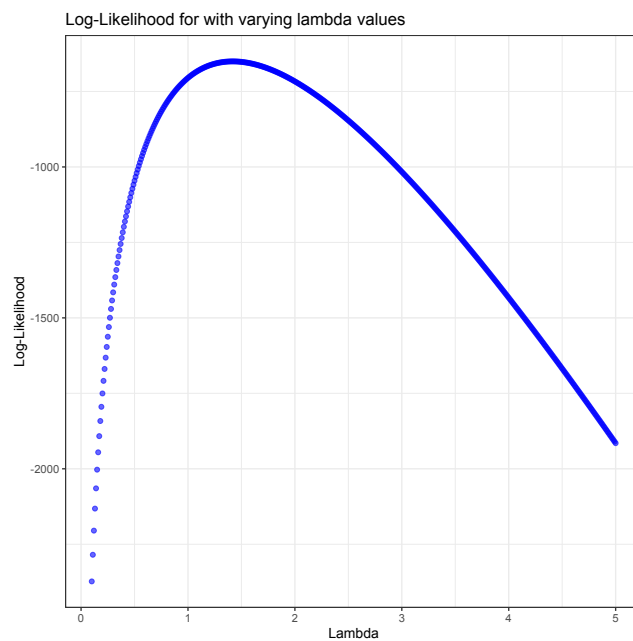


Figure 2: Log-likelihood plot for an exponential distribution with varying  $\lambda$



**1.6.3 Using the plot or otherwise, which estimate for  $\lambda$  is the MLE? Give a reason for your answer.**

As we have seen in the previous question, the maximum likelihood estimation is the value for which the derivative of the log-likelihood with respect to lambda is zero, that is the peak of the curve shown in Figure 2. This can be easily calculated using the code below. The value obtained for  $\hat{\lambda}$  was **1.43**.

```
1 max_ll <- max(log_likelihood_values)
2 max_lambda <- lambda_values[log_likelihood_values == max_ll]
3 print(glue("Lambda value for maximum log-likelihood is
  {max_lambda}"))
```

## 2 Question 2

Suppose that we wish to estimate the parameters of the model:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3}^3 + \varepsilon_i$$

given a sample of size  $n$ .

**2.1 State the type of estimator that needs to be used in this situation and mention two properties of this estimator.**

The appropriate estimator for the given regression model:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3}^3 + \varepsilon_i$$

is the Ordinary Least Squares Estimator. This estimator is used because it is linear in parameters, even though  $x_3^3$  introduces a non-linear transformation. In addition, Ordinary Least Squares minimizes the sum of squared residuals to obtain the best fit for the parameters. Properties of the Ordinary Least Squares estimator include:

- Unbiasedness. The Ordinary Least Squares estimator is unbiased, meaning its expected value equals the true parameter value;  $E[\hat{\beta}] = \beta$ .
- Best Linear Unbiased Estimator. Ordinary Least Squares provides the lowest variance among all linear unbiased estimators, making Ordinary Least Squares the most efficient estimator when errors have constant variance (homoscedasticity).

**2.2 Derive the equations that need to be solved to obtain the required estimates.**

For the given model:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3}^3 + \varepsilon_i$$

The sum of squared residuals will be minimized using ordinary least squares.

$$S = \sum_{i=1}^n (\varepsilon_i = \sum_{i=1}^n y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3}^3)$$

Our aim is to find

$$\arg \max_{\beta_0, \beta_1, \beta_2, \beta_3} S$$

by equating

$$\frac{\partial S}{\partial \beta_0} = 0, \frac{\partial S}{\partial \beta_1} = 0, \frac{\partial S}{\partial \beta_2} = 0, \frac{\partial S}{\partial \beta_3} = 0$$

that is,

$$\begin{aligned} \frac{\partial S}{\partial \beta_0} &= 2 \sum_{i=1}^n (\varepsilon_i = \sum_{i=1}^n y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3}^3) = 0 \\ \frac{\partial S}{\partial \beta_1} &= \sum_{i=1}^n (\varepsilon_i = \sum_{i=1}^n y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3}^3) (-x_{i1}) = 0 \\ \frac{\partial S}{\partial \beta_2} &= \sum_{i=1}^n (\varepsilon_i = \sum_{i=1}^n y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3}^3) (-x_{i2}) = 0 \\ \frac{\partial S}{\partial \beta_3} &= \sum_{i=1}^n (\varepsilon_i = \sum_{i=1}^n y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \beta_3 x_{i3}^3) (-x_{i3}^3) = 0 \end{aligned}$$

rearranging,

$$\begin{aligned} \sum_{i=1}^n y_i &= n\beta_0 + \beta_1 \sum_{i=1}^n x_{i1} + \beta_2 \sum_{i=1}^n x_{i2} + \beta_3 \sum_{i=1}^n x_{i3}^3 \\ \sum_{i=1}^n y_i x_{i1} &= \beta_0 \sum_{i=1}^n x_{i1} + \beta_1 \sum_{i=1}^n x_{i1}^2 + \beta_2 \sum_{i=1}^n x_{i2} x_{i1} + \beta_3 \sum_{i=1}^n x_{i3}^3 x_{i1} \\ \sum_{i=1}^n y_i x_{i2} &= \beta_0 \sum_{i=1}^n x_{i2} + \beta_1 \sum_{i=1}^n x_{i1} x_{i2} + \beta_2 \sum_{i=1}^n x_{i2}^2 + \beta_3 \sum_{i=1}^n x_{i3}^3 x_{i2} \\ \sum_{i=1}^n y_i x_{i3}^3 &= \beta_0 \sum_{i=1}^n x_{i3}^3 + \beta_1 \sum_{i=1}^n x_{i1} x_{i3}^3 + \beta_2 \sum_{i=1}^n x_{i2} x_{i3}^3 + \beta_3 \sum_{i=1}^n x_{i3}^6 \end{aligned}$$

that can be written in matrix form as follows:

$$\begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n y_i x_{i1} \\ \sum_{i=1}^n y_i x_{i2} \\ \sum_{i=1}^n y_i x_{i3}^3 \end{bmatrix} = \begin{bmatrix} n & \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i2} & \sum_{i=1}^n x_{i3}^3 \\ \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i1}^2 & \sum_{i=1}^n x_{i2} x_{i1} & \sum_{i=1}^n x_{i3}^3 x_{i1} \\ \sum_{i=1}^n x_{i2} & \sum_{i=1}^n x_{i1} x_{i2} & \sum_{i=1}^n x_{i2}^2 & \sum_{i=1}^n x_{i3}^3 x_{i2} \\ \sum_{i=1}^n x_{i3}^3 & \sum_{i=1}^n x_{i1} x_{i3}^3 & \sum_{i=1}^n x_{i2} x_{i3}^3 & \sum_{i=1}^n x_{i3}^6 \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \end{bmatrix} \quad (9)$$

Equation 9 needs to be solved to obtain the required estimates. But let us try to move this a bit further. If we set the design matrix  $\mathbf{X}$  as follows:

$$\mathbf{X} = \begin{bmatrix} 1 & x_{11} & x_{12} & x_{13} \\ 1 & x_{21} & x_{22} & x_{23} \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} & x_{n3} \end{bmatrix}$$

We can see that

$$\mathbf{X}^T \mathbf{X} = \begin{bmatrix} n & \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i2} & \sum_{i=1}^n x_{i3} \\ \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i1}^2 & \sum_{i=1}^n x_{i2}x_{i1} & \sum_{i=1}^n x_{i3}^3 x_{i1} \\ \sum_{i=1}^n x_{i2} & \sum_{i=1}^n x_{i1}x_{i2} & \sum_{i=1}^n x_{i2}^2 & \sum_{i=1}^n x_{i3}^3 x_{i2} \\ \sum_{i=1}^n x_{i3} & \sum_{i=1}^n x_{i1}x_{i3} & \sum_{i=1}^n x_{i2}x_{i3} & \sum_{i=1}^n x_{i3}^6 \end{bmatrix}$$

and

$$\mathbf{X}^T \mathbf{Y} = \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n y_i x_{i1} \\ \sum_{i=1}^n y_i x_{i2} \\ \sum_{i=1}^n y_i x_{i3} \end{bmatrix}$$

Therefore Equation 9 can be written as

$$\mathbf{X}^T \mathbf{Y} = \mathbf{X}^T \mathbf{X} \boldsymbol{\beta} \quad (10)$$

so that

$$\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (11)$$

$\mathbf{X}^T \mathbf{X}$  is known as the Gram matrix and represents the relationships among predictor variables in a regression model. Its inverse,  $(\mathbf{X}^T \mathbf{X})^{-1}$ , plays a crucial role in calculating the variance and standard errors of the estimated regression coefficients. Specifically, the diagonal elements of  $(\mathbf{X}^T \mathbf{X})^{-1}$  are used to compute the standard errors of the estimated coefficients. The standard error of  $\hat{\beta}_j$  is given by:

$$SE(\hat{\beta}_j) = \sqrt{\sigma^2 \cdot ((\mathbf{X}^T \mathbf{X})^{-1})_{jj}}$$

where  $\sigma^2$  is the residual variance, and  $((\mathbf{X}^T \mathbf{X})^{-1})_{jj}$  is the diagonal element corresponding to  $\beta_j$ . This formulation ensures that the uncertainty in the coefficient estimates accounts for correlations between predictors, making it a fundamental component in statistical inference for regression models.

**2.3    Generate or source a dataset for which you would use this type of model and fit the model to the data. Present a plot of the fitted model to the data. Comment on the goodness of fit of the model to the data. The R code used for this question should be presented together with the answers. Proper referencing should be provided in the text if the data is sourced.**

Listing 1 creates a synthetic dataset for this examples and fits the specified linear model. It can be summarized as follows:

1. The predictor variable ranges are first defined. The predictor variables are then generated with random noise to introduce variability, which ensures numerical stability in regression computations.
2. The regression coefficients are then specified;  $\beta_0 = 5$ ,  $\beta_1 = 2.5$ ,  $\beta_2 = -1.2$ ,  $\beta_3 = 0.8$
3. The response variable ( $y$ ) is computed as a linear combination of  $x_1$  and  $x_2$ , along with a cubic transformation of  $x_3$  to capture non-linear effects.
4. Random noise is added to the response variable to simulate measurement error and external variability, forcing the model to account for stochastic influences.
5. A multiple regression model is then fitted to estimate the relationships between predictors and the response variable while incorporating the cubic transformation of  $x_3$  to capture non-linear patterns.

```

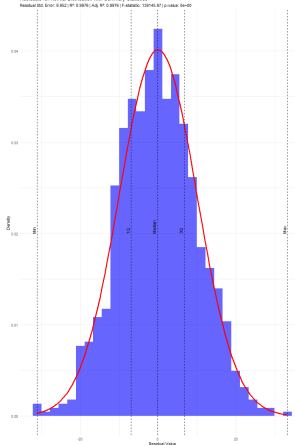
1 set.seed(2023)
2
3 library(ggplot2)
4
5 # Generate data
6
7 number_of_samples <- 1000
8
9 limits_x1 <- c(-10, 10)
10 limits_x2 <- c(-7, 5)
11 limits_x3 <- c(-3, 8)
12
13 x1 <- seq(limits_x1[1], limits_x1[2], length.out =
      number_of_samples) + rnorm(number_of_samples, mean = 0, sd =
      2) # Add slight randomness
14 x2 <- seq(limits_x2[1], limits_x2[2], length.out =
      number_of_samples) + rnorm(number_of_samples, mean = 0, sd =
      2) # Add slight randomness
15 x3 <- seq(limits_x3[1], limits_x3[2], length.out =
      number_of_samples) + rnorm(number_of_samples, mean = 0, sd =
      2) # Add slight randomness
16
17 beta_0 <- 5
18 beta_1 <- 2.5
19 beta_2 <- -1.2
20 beta_3 <- 0.8
21
22 y <- beta_0 + (beta_1 * x1) + (beta_2 * x2) + (beta_3 * x3^3)
23 error <- rnorm(length(y), mean = 0.1, sd = 10) # Random noise
24 y_real <- y + error
25
26
27 model <- lm(y_real ~ x1 + x2 + I(x3^3))
28 print(summary(model))

```

Listing 1: Data generation and model fitting using Ordinary Least Squares

The following table lists the `summary` results that were obtained. Figure 3 shows the actual vs. predicted values for our model. The plot suggests that the model's predictions are very close to the actual values, meaning it captures most of the variance in the data.

Regression Output	Comment
<b>Call</b>	
<code>lm(formula = y_real ~ x1 + x2 + I(x3^3))</code>	Specifies a linear regression where $y$ is predicted using $x_1$ , $x_2$ , and $x_3^3$ . The function <code>I(x3^3)</code> ensures $x_3$ is cubed as a transformation.
<b>Residuals</b>	
Min = -31.031	Smallest residual (largest over-prediction).
1Q = -6.926	First quartile (25% of residuals are below this).

Median = -0.218	Median residual, close to zero suggests unbiased predictions.
3Q = 6.738	Third quartile (75% of residuals are below this).
Max = 33.252	Largest residual (largest under-prediction).
residuals plot (not part of summary but generated subsequently)	
<b>Coefficients</b>	
(Intercept) = 5.44611	$\hat{\beta}_0$
x1 = 2.67591	$\hat{\beta}_1$
x2 = -1.41965	$\hat{\beta}_2$
I(x3^3) = 0.80047	$\hat{\beta}_3$
<b>Standard Errors (Precision of Estimates)</b>	
Intercept SE = 0.39241	Standard error for $\beta_0$ . Smaller SE suggests a reliable estimate.
x1 SE = 0.09603	Standard error for $\beta_1$ . A small SE implies that estimates are stable.
x2 SE = 0.13976	Standard error for $\beta_2$ . Suggests moderate precision but check for multicollinearity.
I(x3^3) SE = 0.00157	Very small SE, indicating high precision and a narrow confidence interval.
<b>t-values (Test Statistic for Significance)</b>	
Intercept t-value = 13.88	Indicates the intercept is statistically significant.
x1 t-value = 27.86	Strong evidence that $x_1$ affects $y$ . Practical significance should also be considered.
x2 t-value = -10.16	Strong evidence that $x_2$ affects $y$ . Multicollinearity should be assessed.
I(x3^3) t-value = 509.81	Extremely strong effect of $x_3^3$ on $y$ . Consider checking residual plots for outliers.
<b>p-values (Significance Levels)</b>	
Intercept p-value < 2e-16	Highly significant ( $p < 0.001$ ).
x1 p-value < 2e-16	Highly significant ( $p < 0.001$ ).

$x^2$ p-value < $2e-16$	Highly significant ( $p < 0.001$ ).
$I(x^3)$ p-value < $2e-16$	Highly significant ( $p < 0.001$ ).
<b>Model Fit Statistics</b>	
Residual standard error = 9.952	Measures average prediction error.
Multiple $R^2 = 0.9976$	Model explains 99.76% of the variance in $y$ .
Adjusted $R^2 = 0.9976$	Adjusted for the number of predictors, still very high.
F-statistic = $1.391 \times 10^5$	Tests overall model significance.
Model p-value < $2.2e-16$	Overall model is highly significant.

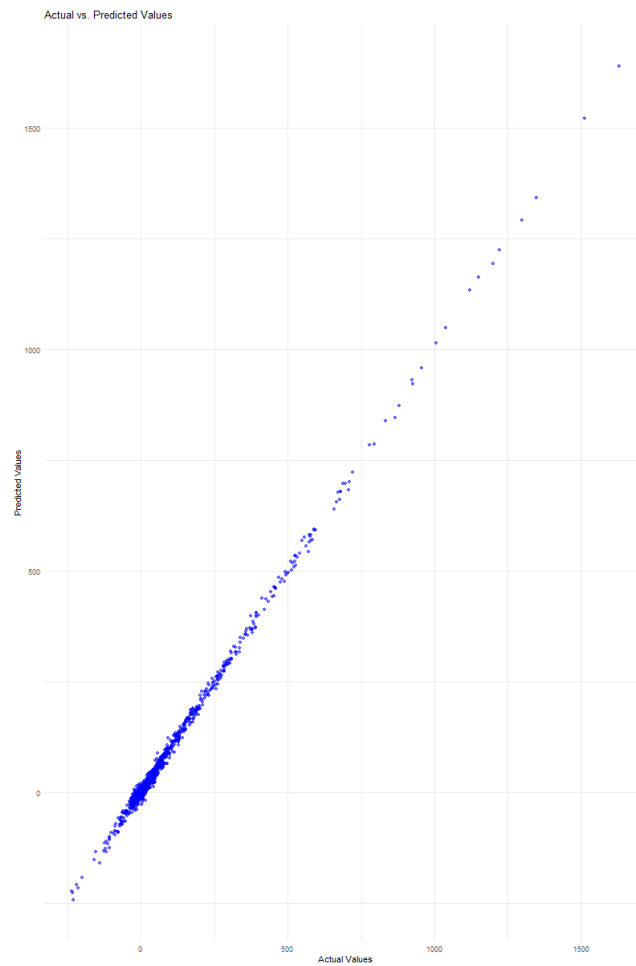


Figure 3: Predicted vs. actual values of the response variable

### 3 Question 3

Let  $x_1, \dots, x_n$  be a random sample selected from a population with a distribution of your choice. [This distribution needs to be different from those used in the lecture notes].

#### 3.1 Derive the maximum likelihood estimator/s of the parameters of the chosen distribution.

For this problem we will examine the famous Pareto distribution that is used to describe a wide range of phenomena. The probability density function for this distribution is given by;

$$f(x; \alpha, x_m) = \begin{cases} \frac{\alpha x_m^\alpha}{x^{\alpha+1}} & x \geq x_m \\ 0 & \text{otherwise} \end{cases} \quad \text{for } \alpha > 0 \quad x_m > 0,$$

Where

- The shape parameter or tail index  $\alpha$  defines thickness of the distribution tail.
- The scale parameter  $x_m$  represents the minimum possible value that random variable  $X$  can take in the distribution.

The likelihood function for this distribution;

$$L(x; \alpha, x_m) = \prod_{i=1}^n \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}}$$

then,

$$\begin{aligned} l(x; \alpha, x_m) &= \sum_{i=1}^n \log \left( \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}} \right) \\ &= \sum_{i=1}^n (\log(\alpha x_m^\alpha) - \log(x_i^{\alpha+1})) \\ &= \sum_{i=1}^n \log(\alpha x_m^\alpha) - \sum_{i=1}^n \log(x_i^{\alpha+1}) \\ &= \sum_{i=1}^n \log(\alpha) + \sum_{i=1}^n \log(x_m^\alpha) - \sum_{i=1}^n \log(x_i^{\alpha+1}) \\ &= n \log(\alpha) + n \alpha \log(x_m) - (\alpha + 1) \sum_{i=1}^n \log(x_i) \end{aligned}$$



As the probability density function is only defined for  $x_i \geq x_m$ , the likelihood is zero iff  $x_m \leq \min(x_1 \dots x_n)$ . So, the maximum likelihood estimate of  $x_m$  is the largest value such that all observed data are  $\geq x_m$ . This implies:

$$\widehat{x}_m = \min(x_1 \dots x_n)$$

Similarly,

$$\frac{\partial l(x; \alpha, x_m)}{\partial \alpha} = \frac{n}{\alpha} + n \log(x_m) - \sum_{i=1}^n \log(x_i)$$

for maximum likelihood

$$\begin{aligned} \frac{n}{\alpha} + n \log(x_m) - \sum_{i=1}^n \log(x_i) &= 0 \\ -\frac{n}{\alpha} - n \log(x_m) + \sum_{i=1}^n \log(x_i) &= 0 \\ -\frac{n}{\alpha} - \sum_{i=1}^n \log(x_m) + \sum_{i=1}^n \log(x_i) &= 0 \\ -\frac{n}{\alpha} + \sum_{i=1}^n \log \frac{x_i}{x_m} &= 0 \end{aligned}$$

Hence;

$$\widehat{\alpha} = \frac{n}{\sum_{i=1}^n \log \frac{x_i}{x_m}}$$

Where  $x_i \geq x_m$  and  $\widehat{x}_m = \min(\mathbf{x})$ , so,

$$\widehat{\alpha} = \frac{n}{\sum_{i=1}^n \log \frac{x_i}{\min(x_1 \dots x_n)}}$$

Hence the maximum likelihood estimators are:

$$\widehat{x}_m = \min(x_1 \dots x_n), \quad \widehat{\alpha} = \frac{n}{\sum_{i=1}^n \log \frac{x_i}{\min(x_1 \dots x_n)}}$$

### 3.2 Find the Cramer-Rao lower bound for the maximum likelihood estimator/s obtained in Q3i).

The likelihood for a single observation

$$L(x; \alpha, x_m) = \frac{\alpha x_m^\alpha}{x^{\alpha+1}}; \quad x \geq x_m$$

The log likelihood

$$l(x; \alpha, x_m) = \log(\alpha) + \alpha \log(x_m) - (\alpha + 1) \log(x)$$

For  $x_m$ , the score function

$$\frac{\partial l(x; \alpha, x_m)}{\partial x_m} = \frac{\alpha}{x_m}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

Taking the second derivative with respect to  $x_m$

$$\frac{\partial^2 l(x; \alpha, x_m)}{\partial x_m^2} = -\frac{\alpha}{x_m^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

The expected value;

$$E \left[ \frac{\partial^2 l(x; \alpha, x_m)}{\partial x_m^2} \right] = -\frac{\alpha}{x_m^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

Fisher information for n samples,

$$I_n(x_m) = \frac{n\alpha}{x_m^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

So CRLB,

$$Var(\widehat{x_m}) \geq \frac{x_m^2}{n\alpha}; \quad x_m > 0, \alpha > 0$$

For  $\alpha$ , the score function

$$\frac{\partial l(x; \alpha, x_m)}{\partial \alpha} = \frac{1}{\alpha} + \log(x_m) - \log(x); \quad x \geq x_m, x_m > 0, \alpha > 0$$

Taking the second derivative with respect to  $\alpha$

$$\frac{\partial^2 l(x; \alpha, x_m)}{\partial \alpha^2} = -\frac{1}{\alpha^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

The expected value;

$$E \left[ \frac{\partial^2 l(x; \alpha, x_m)}{\partial \alpha^2} \right] = -\frac{1}{\alpha^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

Fisher information for n samples,

$$I_n(\alpha) = \frac{n}{\alpha^2}; \quad x \geq x_m, x_m > 0, \alpha > 0$$

So CRLB,

$$Var(\widehat{\alpha}) \geq \frac{\alpha^2}{n}; \quad \alpha > 0$$

**3.3 Does/do the ML estimator/s obtained in Q3i) attain the Cramer-Rao lower bound? Give a reason for your answer.**

We start this discussion by finding  $\mathbb{E}[\hat{\alpha}]$ , where as we have seen

$$\hat{\alpha} = \frac{n}{\sum_{i=1}^n \log \frac{x_i}{x_m}}, x_m > 0$$

where  $\log$  is the natural log, and

$$x_i \sim \text{Pareto}(\alpha, x_m)$$

We focus on the denominator

$$S = \sum_{i=1}^n \log \frac{x_i}{x_m}$$

and understand its distribution so that we can arrive at the estimate of  $\mathbb{E}[\hat{\alpha}]$ ; and so we start by just understanding the distribution of  $\log \frac{X_i}{x_m}$ . If we define

$$Y = \log \frac{X}{x_m}$$

so that

$$X = x_m e^Y$$

The cumulative distribution function of  $Y$  is

$$\begin{aligned} F_Y(y) &= \mathbb{P}(Y \leq y), \forall y \\ &= \mathbb{P}\left(\log \frac{X}{x_m} \leq y\right) \\ &= \mathbb{P}\left(\frac{X}{x_m} \leq e^y\right) \\ &= \mathbb{P}(X \leq x_m e^y) \end{aligned}$$

for a Pareto distribution, the cumulative distribution function,

$$F_X(x) = \mathbb{P}(X \leq x) = 1 - \left(\frac{x_m}{x}\right)^\alpha, x \geq x_m$$

So,

$$\begin{aligned} F_Y(y) &= \mathbb{P}(X \leq x_m e^y) \\ &= 1 - \left(\frac{x_m}{x_m e^y}\right)^\alpha, x \geq x_m \\ &= 1 - e^{-y\alpha}, \alpha \geq 0 \end{aligned}$$

differentiation to obtain the probability distribution function,

$$Y = \log \left( \frac{X}{x_m} \right) \sim \text{Exponential}(\alpha)$$

Moving on to  $S = \sum_{i=1}^n \log \frac{x_i}{x_m}$  where  $\log(x_i/x_m)$  are i.i.d and exponential with rate  $\alpha$ , so  $S$  follows a Gamma distribution.

$$S \sim \text{Gamma}(n, \alpha)$$

The p.d.f. for this Gamma distribution is

$$f_S(s) = \frac{\alpha^n}{\Gamma(n)} s^{n-1} e^{-\alpha s}, \quad s > 0$$

To find  $\mathbb{E}[\hat{\alpha}]$ , since

$$\hat{\alpha} = \frac{n}{S}$$

Then

$$\mathbb{E}[\hat{\alpha}] = n\mathbb{E}\left[\frac{1}{S}\right]$$

Now

$$\begin{aligned} E\left[\frac{1}{S}\right] &= \int_0^\infty \frac{1}{S} f(s) ds \\ &= \int_0^\infty \frac{1}{S} \frac{\alpha^n}{\Gamma(n)} S^{n-1} e^{-\alpha s} ds \\ &= \frac{\alpha^n}{\Gamma(n)} \int_0^\infty \frac{1}{S} S^{n-1} e^{-\alpha s} ds \\ &= \frac{\alpha^n}{\Gamma(n)} \int_0^\infty S^{n-2} e^{-\alpha s} ds \end{aligned}$$

Since

$$\Gamma(n) = \int_0^\infty S^{n-1} e^{-s} dS$$

If we let

$$\begin{aligned} u &= \alpha S \\ \text{so that } S &= \frac{u}{\alpha} \\ \text{and } ds &= \frac{1}{\alpha} du \end{aligned}$$

$$\begin{aligned}
\int_0^\infty S^{n-2} e^{-\alpha s} dS &= \int_0^\infty \left(\frac{u}{\alpha}\right)^{n-2} e^{-u} \frac{1}{\alpha} du \\
&= \frac{1}{\alpha^{n-1}} \int_0^\infty u^{n-2} e^{-u} du \\
&= \frac{1}{\alpha^{n-1}} \Gamma(n-1)
\end{aligned}$$

And therefore,

$$\begin{aligned}
E\left[\frac{1}{S}\right] &= \frac{\alpha^n}{\Gamma(n)} \frac{1}{\alpha^{n-1}} \Gamma(n-1) \\
&= \frac{\alpha \Gamma(n-1)}{\Gamma(n)} \\
&= \frac{\alpha \Gamma(n-1)}{(n-1)\Gamma(n-1)} \\
&= \frac{\alpha}{(n-1)}
\end{aligned}$$

Let us also consider,

$$\begin{aligned}
E\left[\frac{1}{S^2}\right] &= \int_0^\infty \frac{1}{S^2} f(s) ds \\
&= \int_0^\infty \frac{1}{S^2} \frac{\alpha^n}{\Gamma(n)} S^{n-1} e^{-\alpha s} ds \\
&= \frac{\alpha^n}{\Gamma(n)} \int_0^\infty \frac{1}{S^2} S^{n-1} e^{-\alpha s} ds \\
&= \frac{\alpha^n}{\Gamma(n)} \int_0^\infty S^{n-3} e^{-\alpha s} ds
\end{aligned}$$

If we let

$$\begin{aligned}
u &= \alpha S \\
\text{so that } S &= \frac{u}{\alpha} \\
\text{and } ds &= \frac{1}{\alpha} du
\end{aligned}$$

$$\begin{aligned}
\int_0^\infty S^{n-3} e^{-\alpha s} dS &= \int_0^\infty \left(\frac{u}{\alpha}\right)^{n-3} e^{-u} \frac{1}{\alpha} du \\
&= \frac{1}{\alpha^{n-2}} \int_0^\infty u^{n-3} e^{-u} du \\
&= \frac{1}{\alpha^{n-2}} \Gamma(n-2)
\end{aligned}$$

$$\begin{aligned}
E\left[\frac{1}{S^2}\right] &= \frac{\alpha^n}{\Gamma(n)} \frac{1}{\alpha^{n-2}} \Gamma(n-2) \\
&= \frac{\alpha^2 \Gamma(n-2)}{\Gamma(n)} \\
&= \frac{\alpha^2 \Gamma(n-2)}{(n-2)(n-1)\Gamma(n-2)} \\
&= \frac{\alpha^2}{(n-2)(n-1)}
\end{aligned}$$

And therefore, since  $\hat{\alpha} = \frac{n}{S}$

$$\mathbb{E}[\hat{\alpha}] = \frac{n\alpha}{n-1}$$

and

$$\mathbb{E}[\hat{\alpha}^2] = \frac{n^2 \alpha^2}{(n-2)(n-1)}$$

Now,

$$\begin{aligned}
\text{Var}(\hat{\alpha}) &= \mathbb{E}[\hat{\alpha}^2] - \mathbb{E}[\hat{\alpha}]^2 \\
&= \frac{n^2 \alpha^2}{(n-2)(n-1)} - \frac{n^2 \alpha^2}{(n-1)^2} \\
&= n^2 \alpha^2 \left( \frac{(n-1) - (n-2)}{(n-2)(n-1)^2} \right) \\
&= \frac{n^2 \alpha^2}{(n-2)(n-1)^2}
\end{aligned}$$

This variance is greater than the Cramer Rao lower bound as,

$$\frac{n^2 \alpha^2}{(n-2)(n-1)^2} > \frac{\alpha^2}{n}, \forall n > 2$$

We also notice that as  $n \rightarrow \infty$ , the variance approaches  $\frac{\alpha^2}{n}$ , and hence  $\hat{\alpha}$  becomes asymptotically unbiased.

Let us now consider  $\hat{x}_m$ , where we have found out that  $\hat{x}_m = \min(x_1, \dots, x_n)$ , where,

$$x_i \sim \text{Pareto}(\alpha, x_m)$$

If  $Y = \min(X_1, \dots, X_n)$ , the cumulative distribution function,

$$F_Y(y) = 1 - \left( \frac{x_m}{y} \right)^{n\alpha}, \quad y \geq x_m$$

Differentiating to obtain the probability distribution function,

$$\begin{aligned} f_Y(y) &= \frac{d}{dy} \left( 1 - \frac{x_m^{n\alpha}}{y^{n\alpha}} \right), \quad y \geq x_m \\ &= - \left( n\alpha \frac{x_m^{n\alpha}}{y^{n\alpha+1}} \right) \\ &= \frac{n\alpha x_m^{n\alpha}}{y^{n\alpha+1}} \end{aligned}$$

Now,

$$\begin{aligned} \mathbb{E}[\hat{x}_m] &= \mathbb{E}[Y] \\ &= \int_{x_m}^{\infty} y \frac{n\alpha x_m^{n\alpha}}{y^{n\alpha+1}} dy \\ &= n\alpha x_m^{n\alpha} \int_{x_m}^{\infty} \frac{1}{y^{n\alpha}} dy \\ &= n\alpha x_m^{n\alpha} \left[ \frac{y^{-n\alpha+1}}{-n\alpha+1} \right]_{x_m}^{\infty} \end{aligned}$$

$$\text{As } \lim_{y \rightarrow \infty} y^{-n\alpha+1} = 0$$

$$\begin{aligned} &= n\alpha x_m^{n\alpha} \left( \frac{-x_m^{-n\alpha+1}}{-n\alpha+1} \right), \quad n\alpha > 1 \\ &= n\alpha x_m^{n\alpha} \left( \frac{x_m^{1-n\alpha}}{n\alpha-1} \right) \\ &= \frac{n\alpha x_m}{n\alpha-1} \end{aligned}$$

As  $\mathbb{E}[\hat{x}_m] \neq x_m$ ,  $\hat{x}_m = \min(x_1, \dots, x_n)$  is a biased estimate and does not attain the Cramer Rao lower bound.

**3.4 Is/are the ML estimator/s obtained in Q3i) a sufficient statistic for the population parameter/s? Give a reason for your answer.**

Let us consider the sufficiency of  $\hat{x}_m$ . As

$$f(x_i; x_m) = \begin{cases} \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}}, & x_i \geq x_m, \\ 0, & \text{otherwise.} \end{cases}$$

$$\begin{aligned} f(x_1, \dots, x_n; x_m) &= \prod_{i=1}^n \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}}, \quad x_m \leq \min(x_1, \dots, x_n) \\ &= \alpha^n x_m^{n\alpha} \prod_{i=1}^n x_i^{-(\alpha+1)}, \quad x_m \leq \min(x_1, \dots, x_n) \end{aligned}$$

We can rewrite this using an indicator function,

$$\begin{aligned} &= \alpha^n x_m^{n\alpha} \prod_{i=1}^n x_i^{-\alpha-1} \cdot \mathbf{1}_{\{x_m \leq \min(x_1, \dots, x_n)\}} \\ &= \alpha^n x_m^{n\alpha} \cdot \mathbf{1}_{\{x_m \leq \min(x_1, \dots, x_n)\}} \prod_{i=1}^n x_i^{-\alpha-1} \end{aligned}$$

$$\begin{aligned} \text{Let } T(x) &= \min(x_1, \dots, x_n) \\ &= (x_m^{n\alpha} \cdot \mathbf{1}_{\{x_m \leq T(x)\}}) \left( \alpha^n \prod_{i=1}^n x_i^{-\alpha-1} \right) \\ &= g(T(x); x_m) h(x) \end{aligned}$$

So by Neyman-Fisher  $T(x) = \min(x_1, \dots, x_n)$  is a sufficient statistic of  $x_m$   
Considering also the sufficiency of  $\hat{\alpha}$

$$f(x_i; \alpha) = \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}}, \quad x_i \geq x_m$$



$$\begin{aligned}
f(x_1, \dots, x_n; \alpha) &= \prod_{i=1}^n \frac{\alpha x_m^\alpha}{x_i^{\alpha+1}} \\
&= \alpha^n x_m^{n\alpha} \prod_{i=1}^n x_i^{-\alpha-1} \\
&= \alpha^n e^{\log(x_m^{n\alpha})} e^{\log(\prod_{i=1}^n x_i^{-\alpha-1})} \\
&= \alpha^n e^{n\alpha \log(x_m)} e^{(-\alpha-1) \sum_{i=1}^n \log(x_i)} \\
&= \alpha^n e^{n\alpha \log(x_m) + (-\alpha-1) \sum_{i=1}^n \log(x_i)} \\
\text{Let } T(x) &= \sum_{i=1}^n \log(x_i) \\
&= \left( \alpha^n e^{n\alpha \log(x_m) + (-\alpha-1)T(x)} \right) (1) \\
&= g(T(x); x_m) h(x)
\end{aligned}$$

So  $\sum_{i=1}^n \log(x_i)$  is a sufficient statistic of  $\alpha$ . Furthermore,

$$\begin{aligned}
\hat{\alpha} &= \frac{n}{\sum_{i=1}^n \log\left(\frac{x_i}{x_m}\right)} \\
&= \frac{n}{\sum_{i=1}^n (\log(x_i) - \log(x_m))} \\
&= \frac{n}{\sum_{i=1}^n \log(x_i) - \sum_{i=1}^n \log(x_m)}
\end{aligned}$$

Since  $T(x)$  is a sufficient statistic for  $\alpha$  and  $\hat{\alpha}$  is a function of  $T(x)$ , it follows that  $\hat{\alpha}$  is also sufficient for  $\alpha$ .

### 3.5 Why are maximum likelihood estimators considered to be desirable estimators? Mention one situation where a maximum likelihood estimator might not be optimal.

Maximum likelihood estimators are considered desirable estimators due to several properties,

- **Consistency.** As the sample size increases, the maximum likelihood estimator converges in probability to the parameter's actual value.
- **Asymptotic Normality.** The distribution of the maximum likelihood estimator approaches a normal distribution centred on the actual parameter value.

- **Asymptotic Efficiency.** Among all consistent and asymptotically normal estimators, the maximum likelihood estimator achieves the lowest possible asymptotic variance; it attains the Cramér-Rao Lower Bound asymptotically.
- **Invariance.** If  $\hat{\theta}$  is the maximum likelihood estimator for  $\theta$ , then  $g(\hat{\theta})$  is the maximum likelihood estimator for  $g(\theta)$ .
- **Generality.** Maximum likelihood estimators can be applied to various distributions and likelihood models, even in complex or multivariate settings.

Maximum likelihood estimators are not always optimal, particularly in small samples.

In the Pareto( $\alpha, x_m$ ) case examined in this question:

The Maximum likelihood estimator for  $x_m$  is:

$$\hat{x}_m = \min(x_1, \dots, x_n)$$

Although this is the Maximum likelihood estimator, it is biased, and we showed:

$$\mathbb{E}[\hat{x}_m] = \frac{n\alpha}{n\alpha - 1} x_m \neq x_m$$

Moreover,  $\hat{x}_m$  does not attain the Cramér-Rao lower bound, and its bias persists even in large samples.

This illustrates a situation where the Maximum likelihood estimator does not perform optimally, especially in small samples: it is biased, inefficient, and may not be the best choice if an unbiased or minimum variance estimator is available.

## 4 Question 4 - Jackknife and bootstrap

Consider 50 observations of bivariate pair  $(X, Y)$  in `resampling.xlsx`. Use the `nls` command in R to estimate the non-linear regression  $Y = \frac{aX}{b+X} + \epsilon$ .

The code in Listing 2 performs non-linear regression on the dataset. The resulting plots are presented in Figure 4. The estimated parameters are  $\hat{a} = 14.56$  and  $\hat{b} = 7.10$ .

```

1 library(openxlsx)
2 library(ggplot2)
3
4 # load file
5 script_dir <- getwd()
6 file_path <- file.path(script_dir, "resampling.xlsx")
7 df <- read.xlsx(file_path, colNames = TRUE)
8
9 print(c("number of rows: ", nrow(df)))
10
11 # estimate the parameters of the model
12 init_a <- 1
13 init_b <- 1
14
15 nls_model <- nls(y ~ (a * x) / (b + x),
16 data = df,
17 start = list(a = init_a, b = init_b))
18
19
20 estimated_params <- coef(nls_model)
21 a_hat <- estimated_params["a"]
22 b_hat <- estimated_params["b"]
23 cat("Estimated a:", a_hat, "\n")
24 cat("Estimated b:", b_hat, "\n")
25
26 # predict the values of y
27 df$Predicted <- predict(nls_model)
28 print(head(df))
29
30 # plot the data
31 p <- ggplot(df, aes(x = x , y = y)) +
32 geom_point(color = "blue", alpha = 0.5) +
33 geom_line(aes(
34     y = Predicted),
35     color = "red",
36     linewidth = 1) +
37 labs(title = "Nonlinear Regression: Y = (aX) / (b+X)",
38 x = "X", y = "Y") +
39 theme_minimal()
40
41 print(p)

```

Listing 2: Non linear regression code in R

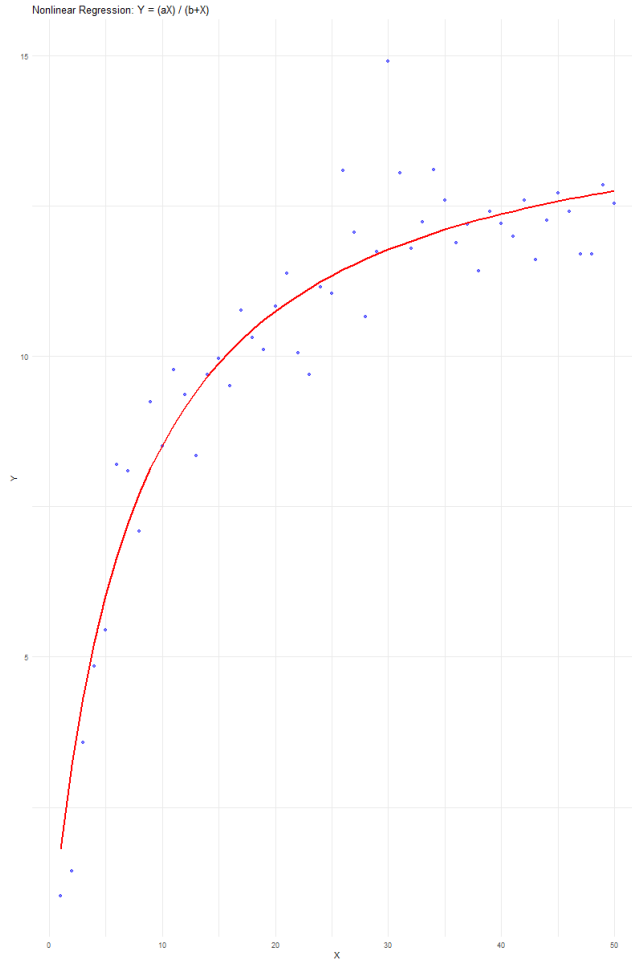


Figure 4: Non-linear regression fit: observed vs. predicted values

#### 4.1 Construct a computer code in R to find the Jackknife and Bootstrap estimators of $a$ and $b$ . In the case of Jackknife, section randomly the sampling into 5 partitions of size 10. In the case of - Bootstrap, generate 1000 samples of size 100 with replacement.

The code in Listing 3 executes the following steps on the data to implement Jackknife resampling with non linear regression. The resulting plots are presented in Figure 5. The estimated parameters are  $\hat{a}_{jk} = 14.504$  and  $\hat{b}_{jk} = 6.996$ . The code executes the following steps to estimate the parameters:

1. **Shuffle the dataset:** We randomly shuffle the data to remove any or-

dering bias:

2. **Divide the data into  $m$  Jackknife partitions:** We split the dataset into  $m = 5$  partitions, each missing a unique subset of 5 elements.
3. **Fit the Non-linear Least Squares model for each Jackknife sample:** We fit a non-linear regression model to each Jackknife sample using Non-linear Least Squares to estimate parameters  $a$  and  $b$ . The model is defined as:

$$Y = \frac{aX}{b + X} \quad (12)$$

and is refitted for each sample  $S_{-a}$ , which excludes partition  $P_a$ .

4. **Compute Jackknife bias-corrected estimates:** The Jackknife estimate for each parameter is calculated using the bias correction formula:

$$\hat{\theta}_{\text{jack}} = m\hat{\theta} - (m-1)\hat{\theta}_{(-a)} \quad (13)$$

where:

- $m = 5$  is the number of partitions.
  - $\hat{\theta}$  is the parameter estimate from the full dataset.
  - $\hat{\theta}_{(-a)}$  is the parameter estimate from the jackknife sample with partition  $a$  removed.
5. **Compute final Jackknife estimates for  $a$  and  $b$ :** The final Jackknife estimates for  $a$  and  $b$  are obtained by averaging the bias-corrected values across all jackknife samples:

$$\hat{a}_{jk} = \frac{1}{m} \sum_{a=1}^m \hat{a}_{\text{jack},a}, \quad \hat{b}_{jk} = \frac{1}{m} \sum_{a=1}^m \hat{b}_{\text{jack},a} \quad (14)$$

```

1 partition_size <- 5
2
3 #shuffle the dataframe
4 set.seed(123)
5 df_shuf <- df[sample(nrow(df)), ]
6
7 # Generate jackknife samples by removing each fold of 5 elements
8 # lapply applies a function to each element of a list
9 # my list is from 1:5
10 # the function will
11 # for a = 1 remove element 1 to 5 (5*(1-1)+1):(5*1)
12 # and so on
13 # note the - sign -- I am removing the elements
14 # so the return for each a is y without the elements 1 to 5, 6 to
    10, etc.
15 jackknife_samples <- lapply(1:partition_size,
16 function(a) df_shuf[-((partition_size * (a - 1) +
    1):(partition_size * a)), ])
17
18 # we have calculated theta_hat_m before
19 theta_hat_m <- estimated_params
20
21 theta_m_a <- function(data) {
22     model <- nls(y ~ (a * x) / (b + x),
23     data = data,
24     start = list(a = theta_hat_m["a"],
25     b = theta_hat_m["b"]))
26     return(coef(model)) }
27
28 # jackknife estimator for each partition
29 nlsjk <- sapply(jackknife_samples, function(y_a) partition_size *
    theta_hat_m - (partition_size - 1) * theta_m_a(y_a))
30
31 #evaluating the jackknife estimator of the parameters
32 jackknife_estimates <- rowMeans(nlsjk)
33
34 a_hat_jk <- jackknife_estimates["a"]
35 b_hat_jk <- jackknife_estimates["b"]
36
37 df$predicted_jk <- (a_hat_jk * df$x) / (b_hat_jk + df$x)
38
39 # Plot with Jackknife predictions and legend
40 p_jk <- ggplot(df, aes(x = x, y = y)) +
41 geom_point(color = "blue", alpha = 0.5, size = 3) +
42 geom_line(aes(y = Predicted, color = "Full Sample Prediction"),
43 linewidth = 1, linetype = "dashed") +
44 geom_line(aes(y = predicted_jk, color = "Jackknife Prediction"),
45 linewidth = 1) +
46 labs(title = "Nonlinear Regression: Full Sample vs. Jackknife",
47 x = "X", y = "Y", color = "Legend") +
48 theme_minimal() +
49 scale_color_manual(values = c("Full Sample Prediction" = "red",
50 "Jackknife Prediction" = "green"))

```

Listing 3: Jackknife resampling code in R

The resulting plot is shown below in Figure 5

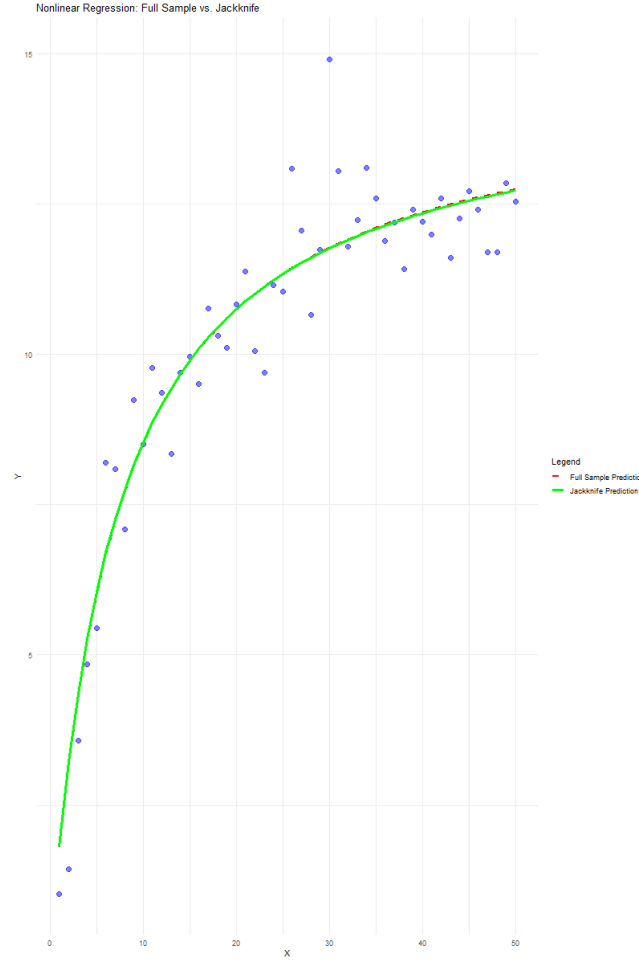


Figure 5: Non-linear regression fit: observed vs. predicted values including Jackknife predictions

The code in Listing 4 executes the following steps on the data to implement Bootstrap resampling with non linear regression. The resulting plots are presented in Figure 6. The estimated parameters are  $\hat{a}_{bs} = 14.566$  and  $\hat{b}_{bs} = 7.110$ . The code executes the following steps to estimate the parameters:

- **Generate Bootstrap Samples:** WE create 1000 resampled datasets of size 100 by drawing with replacement from the 50 original observations.
- **Fit a Non-linear Regression Model:** For each bootstrap sample, we estimate parameters  $a$  and  $b$  using Non-linear Least Squares with the model.

- **Compute Bootstrap Estimates:** The final bootstrap estimates are obtained by averaging the parameter estimates from all bootstrap samples:
- **Predict Values Using Bootstrap Estimates:** Using the estimated parameters  $\hat{a}_{\text{bs}}, \hat{b}_{\text{bs}}$ , we compute the predicted values:

$$\hat{y}_{\text{bs}} = \frac{\hat{a}_{\text{bs}}x}{\hat{b}_{\text{bs}} + x} \quad (15)$$



```

1 num_samples <- 1000
2 sample_size <- 100
3
4 # 1000 bootstrap samples of size 100 with replacement
5 bootstrap_samples <- lapply(1:num_samples, function(i)
6   df[sample(nrow(df), sample_size, replace = TRUE), ])
7
8 fit_bootstrap_nls <- function(data) {
9   model <- nls(y ~ (a * x) / (b + x),
10    data = data,
11    start = list(a = 1, b = 1)) # Initial guesses
12   return(coef(model))
13 }
14
15 # Apply NLS to each bootstrap sample
16 nlsbs <- lapply(bootstrap_samples, fit_bootstrap_nls)
17
18 # Convert list of bootstrap estimates to a matrix
19 bootstrap_estimates <- do.call(rbind, nlsbs)
20 colnames(bootstrap_estimates) <- c("a", "b")
21
22 # Compute mean estimates for a and b
23 a_hat_bs <- mean(bootstrap_estimates[, "a"], na.rm = TRUE)
24 b_hat_bs <- mean(bootstrap_estimates[, "b"], na.rm = TRUE)
25
26 # Print results
27 cat("Bootstrap Estimated a:", a_hat_bs, "\n")
28 cat("Bootstrap Estimated b:", b_hat_bs, "\n")
29
30 df$predicted_bs <- (a_hat_bs * df$x) / (b_hat_bs + df$x)
31
32
33 # Plot with Jackknife predictions and legend
34 p_bs <- ggplot(df, aes(x = x, y = y)) +
35   geom_point(color = "blue", alpha = 0.5, size = 3) +
36   geom_line(aes(y = Predicted, color = "Full Sample Prediction"),
37     linewidth = 1, linetype = "dashed") +
38   geom_line(aes(y = predicted_jk, color = "Jackknife Prediction"),
39     linewidth = 1) +
40   geom_line(aes(y = predicted_bs, color = "Bootstrap Prediction"),
41     linewidth = 1) +
42   labs(title = "Nonlinear Regression: Full Sample vs. Jackknife vs.
43     Bootstrap",
44     x = "X", y = "Y", color = "Legend") +
45   theme_minimal() +
46   scale_color_manual(values = c("Full Sample Prediction" = "red",
47     "Jackknife Prediction" = "green",
48     "Bootstrap Prediction" = "blue"))

```

Listing 4: Bootstrap resampling code in R

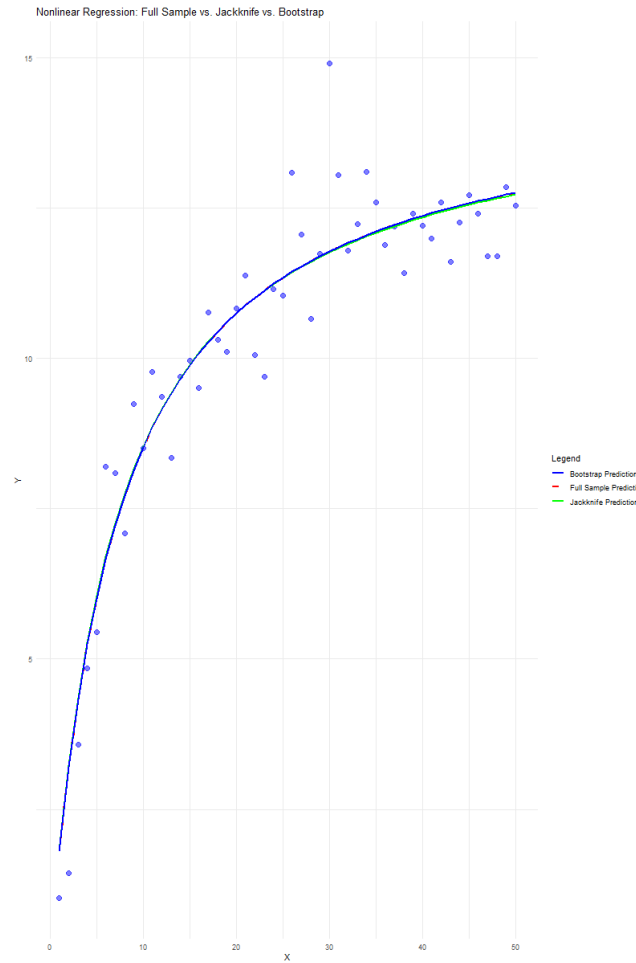


Figure 6: Non-linear regression fit: observed vs. predicted values including Jackknife and Bootstrap predictions

**4.2 For the Jackknife estimator, find a 95% confidence interval using the normal distribution and the t-distribution. For the Bootstrap estimator, find a 95% normal, t and empirical confidence intervals.**

The following results were obtained for the Jackknife resampling method:

## 5 Question 5 – The EM Algorithm

Consider a univariate  $K$ -Gaussian mixture model with probability density function:

Method	Confidence Interval for $a$	Confidence Interval for $b$
<b>Jackknife Resampling</b>		
Normal Distribution	[14.14397, 14.86412]	[6.356596, 7.63524]
t-Distribution	[13.99397, 15.01412]	[6.090267, 7.90157]
<b>Bootstrap Resampling</b>		
Normal Distribution	[14.07722, 15.05515]	[6.111358, 8.109172]
t-Distribution	[14.07663, 15.05575]	[6.110146, 8.110384]
Empirical Distribution	[14.08458, 15.08578]	[6.132766, 8.113393]

Table 2: Confidence Intervals for Parameters  $a$  and  $b$  Using Jackknife and Bootstrap Methods

$$f(x) = \sum_{l=1}^K \pi_l \phi(x, \mu_l, \sigma_l)$$

such that  $\sum_{l=1}^K \pi_l = 1$  and  $\pi_l > 0$  for all  $l$ , and where  $\phi(x, \mu, \sigma)$  is the Gaussian density function. The EM algorithm for this works as follows:

1. Initialise  $\mu_1^{(0)}, \dots, \mu_K^{(0)}, \sigma_1^{(0)}, \dots, \sigma_K^{(0)}, \pi_1^{(0)}, \dots, \pi_K^{(0)}$ .

2. Let

$$\gamma_n^{(j,k)} = \frac{\pi_k \phi(x_n | \mu_k^{(j-1)}, \sigma_k^{(j-1)})}{\sum_{i=1}^K \pi_i \phi(x_n | \mu_i^{(j-1)}, \sigma_i^{(j-1)})}.$$

3. Let

$$\mu_k^{(j)} = \frac{1}{N_k} \sum_{n=1}^N \gamma_n^{(j,k)} x_n,$$

$$\sigma_k^{(j)} = \sqrt{\frac{1}{N_k} \sum_{n=1}^N \gamma_n^{(j,k)} (x_n - \mu_k^{(j)})^2},$$

and

$$\pi_k^{(j)} = \frac{N_{jk}}{N},$$

where

$$N_{jk} = \sum_{n=1}^N \gamma_n^{(j,k)}.$$

### 5.1 Simulate 1000 readings from a mixture Gaussian distribution with 3 or more Gaussians.

The following function generalizes the code provided in the question so that an arbitrary number of samples are generated from any number of Gaussian distributions. The function also lists the number of samples selected from each

Gaussian to ensure that acceptable proportions were attained for each sample and plots a distribution of the data and plots of the Gaussians.

```

1 library(ggplot2)
2
3 generate_samples <- function(
4   mixing_coefficients,
5   means,
6   standard_deviations,
7   number_of_samples = 1000) {
8
9   # should check that lengths are equal
10
11   data <- c()
12   choices_count <- rep(0, length(mixing_coefficients))
13
14   # select one of the gaussian distributions according
15   # to the mixing coefficients
16   choices <- sample(
17     seq_along(mixing_coefficients),
18     size = number_of_samples,
19     prob = mixing_coefficients,
20     replace = TRUE)
21
22   # let us see that the number of selections make sense
23   for (i in 1:number_of_samples){
24     choices_count[choices[i]] <-
25       choices_count[choices[i]] + 1
26   }
27   print(choices_count)
28
29   # for each selection, sample from the gaussian
30   data <- c(
31     data,
32     rnorm(
33       n = number_of_samples,
34       mean = means[choices],
35       sd = standard_deviations[choices]))
36
37   # plot histogram and gaussian curves
38   df <- data.frame(data)
39
40   p <- ggplot(df, aes(x = data)) +
41     geom_histogram(
42       aes(y = ..density..),
43       bins = 30,
44       fill = "blue",
45       alpha = 0.6) +
46     stat_function(fun = function(x) {
47       Reduce('+', lapply(1:length(means), function(i) {
48         dnorm(
49           x = x,
50           mean = means[i],
51           sd = standard_deviations[i]) *
52           mixing_coefficients[i]
53         })
54       })
55     }, color = "red") +
56     labs(title = "Histogram of Mixture of Gaussians",
57          x = "Value",
58          y = "Density") +
59     theme_bw()
60
61   print(p)
62 }

```

Listing 5: Gaussian mixture sample generation code in R

Data from the mixed Gaussian distributions was subsequently generated using the parameters below. The plot that was obtained as a result of this process is shown in Figure 7

$\pi_1 = 0.2$	$\mu_1 = 6$	$\sigma_1 = 2.0$
$\pi_2 = 0.5$	$\mu_2 = 0$	$\sigma_2 = 1.0$
$\pi_3 = 0.3$	$\mu_3 = -7$	$\sigma_3 = 1.5$

```

1 mixing_coefficients <- c(0.2, 0.5, 0.3)
2 means <- c(6, 0, -7)
3 standard_deviations <- c(2, 1, 1.5)
4
5 generate_samples(mixing_coefficients, means,
  standard_deviations)

```

Listing 6: Generation of data for this question

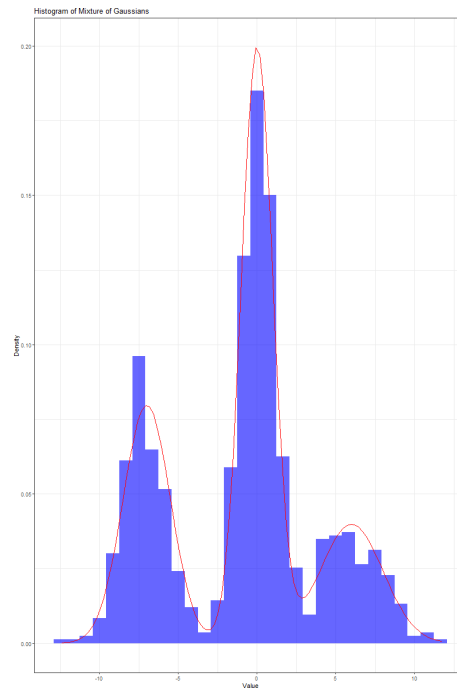


Figure 7: Distribution of generated data

## 5.2 Determine initial values $\mu_1^{(0)}, \dots, \mu_K^{(0)}, \sigma_1^{(0)}, \dots, \sigma_K^{(0)}, \pi_1^{(0)}, \dots, \pi_K^{(0)}$ using a K-means clustering approach or otherwise.

The function in Listing 7 is a custom implementation of a k-means algorithm to initialize parameters( $\mu^{(0)}$ ,  $\sigma^{(0)}$ , and  $\pi^{(0)}$ ) for a Gaussian mixture model. Its salient features are the following:

- After the initial centroids are randomly selected, the k-means algorithm iteratively assigns the data point to the closest centroid based on the absolute distance. The cluster centroids are then updated as the means of the points assigned to each cluster until the change in centroids is small or the threshold number of iterations is reached.
- The means of each centroid is, as we have discussed above, the centroid of each cluster.
- the standard deviation is calculated as follows

$$\sigma_j = \begin{cases} \sqrt{\frac{1}{n_j} \sum_{x_i \in C_j} (x_i - \mu_j)^2}, & \text{if } n_j > 0 \\ 0, & \text{otherwise} \end{cases}$$

Where:

- $\sigma_j$  is the standard deviation for cluster  $j$ ,
- $C_j$  is the set of points in cluster  $j$ ,
- $n_j$  is the number of points in cluster  $j$ ,
- $x_i$  are the individual data points in cluster  $j$ ,
- $\mu_j$  is the centroid (mean) of cluster  $j$ ,
- The initial values for the mixing coefficients of the Gaussian Mixture Model are computed as:

$$\pi_j = \begin{cases} \frac{n_j}{N}, & \text{if } n_j > 0 \\ 0, & \text{otherwise} \end{cases}$$

Where:

- $\pi_j$  is the mixing coefficient for cluster  $j$ ,
- $n_j$  is the number of data points in cluster  $j$ ,
- $N$  is the total number of data points in the dataset,

```

1 initial_values_knn <- function(data, k = 3) {
2   set.seed(42) # For reproducibility
3
4   # Randomly select k initial centroids
5   centroids <- sample(x = data, size = k, replace = FALSE)
6
7   # Initialize empty clusters
8   clusters <- vector(mode = "list", length = k)
9
10  for (iteration in 1:100) {
11    # Reset clusters
12    clusters <- vector(mode = "list", length = k)
13
14    # Assign each data point to the closest centroid
15    for (item in data) {
16      distances <- abs(item - centroids)
17      closest_centroid <- which.min(distances)
18      clusters[[closest_centroid]] <-
19        c(clusters[[closest_centroid]], item)
20    }
21
22    # Compute new centroids
23    new_centroids <- sapply(1:k, function(i) {
24      if (length(clusters[[i]]) > 0) {
25        mean(clusters[[i]])
26      } else {
27        centroids[i] # Keep old centroid
28        if no points are assigned
29      }
30    })
31
32    # Check for convergence
33    if (max(abs(new_centroids - centroids)) < 0.0001) {
34      break
35    }
36
37    centroids <- new_centroids
38
39    # Compute standard deviations
40    clusters_standard_devs <- sapply(1:k,
41      function(cluster_idx) {
42        if (length(clusters[[cluster_idx]]) > 0) {
43          sqrt(sum((clusters[[cluster_idx]] -
44            centroids[cluster_idx])^2) /
45            length(clusters[[cluster_idx]]))
46        } else {
47          0
48        }
49      })
50
51    # Compute mixing coefficients for each cluster
52    mixing_coefficients <- sapply(1:k, function(cluster_idx) {
53      length(clusters[[cluster_idx]]) / length(data)
54    })
55
56    return(list(
57      centroids = centroids,
58      standard_devs = clusters_standard_devs,
59      mixing_coefficients = mixing_coefficients))
60  }

```

Listing 7: k-means algorithm to compute the initial values of the mixed Gaussian model parameters



The results obtained from this function are as follows:

$\pi_1 = 0.179$	$\mu_1 = 6.353$	$\sigma_1 = 1.685$
$\pi_2 = 0.545$	$\mu_2 = 0.104$	$\sigma_2 = 1.107$
$\pi_3 = 0.276$	$\mu_3 = -6.942$	$\sigma_3 = 1.508$

Table 3: Estimated parameters for the initial values of Gaussian mixture model

**5.3 Run the EM algorithm for a number of iterations. Print  $\mu_1^{(j)}, \dots, \mu_k^{(j)}, \sigma_1^{(j)}, \dots, \sigma_k^{(j)}, \pi_1^{(j)}, \dots, \pi_k^{(j)}$  for each iteration, and also the log-likelihood, which is given by:  $\sum_{n=1}^N \ln \left( \sum_{l=1}^K \phi(x_n | \mu_l^{(j)}, \sigma_l^{(j)}) \right)$ . Determine when to stop the EM algorithm, either via a maximum number of iterations or through a convergence criterion. However, ensure that the EM algorithm has converged. Plot the trajectory of the estimates and the likelihood by iteration to illustrate this.**

We start by examining the code created to execute this question, which is presented below in four listings.

- Listing 8 contains the estimation step code that computes the responsibility of each Gaussian component for each data point as:

$$\gamma_{n,k} = \frac{\pi_k \phi(x_n | \mu_k, \sigma_k)}{\sum_{j=1}^K \pi_j \phi(x_n | \mu_j, \sigma_j)}$$

Where:

- $\gamma_{n,k}$  is the responsibility of Gaussian  $k$  for data point  $x_n$ .
- $\pi_k$  is the mixing coefficient for Gaussian  $k$ .
- $\phi(x_n | \mu_k, \sigma_k)$  is the Gaussian probability density function:

$$\phi(x_n | \mu_k, \sigma_k) = \frac{1}{\sigma_k \sqrt{2\pi}} \exp \left( -\frac{(x_n - \mu_k)^2}{2\sigma_k^2} \right).$$

- Listing 9 illustrates the maximization step of the EM algorithm that updates the parameters as follows:
  - We update the mixing coefficients to calculate the proportion of data points that belong to a given Gaussian distribution:

$$\pi_k^{(j)} = \frac{N_k^{(j)}}{N}$$

Where:

$$N_k^{(j)} = \sum_{n=1}^N \gamma_{n,k}^{(j)}$$

Is the total responsibility weight assigned to Gaussian  $k$ ?

- We update the means to compute the weighted mean of the data points assigned to each Gaussian:

$$\mu_k^{(j)} = \frac{\sum_{n=1}^N \gamma_{n,k}^{(j)} x_n}{N_k^{(j)}}$$

- We update the standard deviations to calculate the spread of the data points around the updated mean for each Gaussian:

$$\sigma_k^{(j)} = \sqrt{\frac{\sum_{n=1}^N \gamma_{n,k}^{(j)} (x_n - \mu_k^{(j)})^2}{N_k^{(j)}}}$$

- We then calculate the log-likelihood function for our Gaussian mixture model using the code in Listing 10 using the suggested formulation:

$$\mathcal{L} = \sum_{n=1}^N \ln \left( \sum_{k=1}^K \pi_k \phi(x_n | \mu_k, \sigma_k) \right)$$

Where:

- $\mathcal{L}$  is the log-likelihood of the data.
- $K$  is the number of Gaussian components.
- $N$  is the number of data points.
- $\pi_k$  is the mixing coefficient for Gaussian  $k$ .
- $\phi(x_n | \mu_k, \sigma_k)$  is the Gaussian probability density function:

$$\phi(x_n | \mu_k, \sigma_k) = \frac{1}{\sigma_k \sqrt{2\pi}} \exp \left( -\frac{(x_n - \mu_k)^2}{2\sigma_k^2} \right)$$

- Listing 11 shows the execution of the EM algorithm, starting from the generation of data to the estimation of the initial values and ending with the actual estimates using the EM algorithm. We notice that EM is allowed a maximum of execution 100 steps, but optimization will stop if the change in log-likelihood is smaller than  $10^{-5}$ .

```

1 expectation_step <- function(data, means, standard_deviations,
2   mixing_coefficients) {
3     number_of_gaussians <- length(mixing_coefficients)
4
5     # Initialize gamma matrix
6     gamma <- matrix(0, nrow = length(data), ncol =
7       number_of_gaussians)
8
9     # Calculate denominator (total probability for each data
10    point)
11    den_total <- 0
12    for (k in 1:number_of_gaussians) {
13      den_total <- den_total + mixing_coefficients[k] *
14        dnorm(data, mean = means[k], sd =
15          standard_deviations[k])
16    }
17
18    # Calculate numerator and compute gamma
19    for (k in 1:number_of_gaussians) {
20      gamma[, k] <- (mixing_coefficients[k] *
21        dnorm(data, mean = means[k], sd =
22          standard_deviations[k])) / den_total
23    }
24
25    return(gamma)
26  }

```

Listing 8: Estimation step code in R

```

1 maximization_step <- function(data, gamma, means,
2   standard_deviations, mixing_coefficients) {
3
4     no_gaussians <- length(mixing_coefficients)
5     m <- length(data)
6
7     # Compute cluster responsibilities
8     m_c <- colSums(gamma) # Sum of responsibilities for each
      Gaussian
9
10    # Compute new mixing coefficients
11    new_mixing_coefficients <- m_c / m
12
13    # Initialize new means and standard deviations
14    new_means <- numeric(no_gaussians)
15    new_standard_deviations <- numeric(no_gaussians)
16
17    # Compute new means and standard deviations for each
      Gaussian
18    for (k in 1:no_gaussians) {
19      new_means[k] <- sum(gamma[, k] * data) / m_c[k]
20      new_standard_deviations[k] <- sqrt(sum(gamma[, k]
      * (data - means[k])^2) / m_c[k])
21    }
22
23    return(list(
24      means = new_means,
25      standard_devs = new_standard_deviations,
26      mixing_coefficients = new_mixing_coefficients
27    ))
28 }

```

Listing 9: Maximization step code in R

```

1 log_likelihood <- function(data, means, standard_deviations,
2   mixing_coefficients) {
3     number_of_gaussians <- length(mixing_coefficients)
4
5     # Initialize likelihood matrix
6     likelihood <- matrix(0, nrow = length(data), ncol =
7       number_of_gaussians)
8
9     # Compute likelihood for each Gaussian component
10    for (k in 1:number_of_gaussians) {
11      likelihood[, k] <- mixing_coefficients[k] *
12        dnorm(data, mean = means[k], sd =
13          standard_deviations[k])
14    }
15
16    # Compute the log-likelihood
17    log_likelihood_value <- sum(log(rowSums(likelihood)))
18
19    return(log_likelihood_value)
20 }

```

Listing 10: Log-likelihood code in R

```

1 mixing_coefficients <- c(0.2, 0.5, 0.3)
2 means <- c(6, 0, -7)
3 standard_deviations <- c(2, 1, 1.5)
4
5 # generate the data
6 data <- generate_samples(mixing_coefficients, means,
7                           standard_deviations)
8
9 # initial values
10 kmeans_ret <- initial_values_kmeans(data)
11
12 centroids <- kmeans_ret$centroids
13 standard_devs <- kmeans_ret$standard_devs
14 mixing_coefficients <- kmeans_ret$mixing_coefficients
15
16 print("initial values")
17 print(centroids)
18 print(standard_devs)
19 print(mixing_coefficients)
20
21 log_likelihoods <- c()
22 for (i in 1:100) {
23     gamma <- expectation_step(data, centroids, standard_devs,
24                               mixing_coefficients)
25
26     max_ret <- maximization_step(data, gamma, centroids,
27                                  standard_devs, mixing_coefficients)
28
29     centroids <- max_ret$means
30     standard_devs <- max_ret$standard_devs
31     mixing_coefficients <- max_ret$mixing_coefficients
32
33     ll <- log_likelihood(data, means, standard_devs,
34                          mixing_coefficients)
35
36     log_likelihoods <- c(log_likelihoods, ll)
37
38     if (i>2 && abs(ll - log_likelihoods[i-1]) < 1e-5) {
39         print("converged")
40         break
41     }
42 }
43 # form string
44 iteration_result_str <- paste( "iteration: ", i)
45 for (j in 1:length(centroids)) {
46     iteration_result_str <-
47         paste(iteration_result_str, " c",j,": ",
48               format(centroids[j],3))
49     iteration_result_str <-
50         paste(iteration_result_str, " s",j,": ",
51               format(standard_devs[j],3))
52     iteration_result_str <-
53         paste(iteration_result_str, " m",j,": ",
54               format(mixing_coefficients[j],3))
55 }
56 print(iteration_result_str)
57 }

```

Listing 11: Execution code for this question

The parameters obtained after each iteration are shown in Table 4. The algorithm converged after 28 iterations. A plot of the log likelihood at each iteration can be observed in Figure 8

Step	$\pi_1$	$\sigma_1$	$\mu_1$	$\pi_2$	$\sigma_2$	$\mu_2$	$\pi_3$	$\sigma_3$	$\mu_3$	$\mathcal{L}$
1	6.259	1.780	0.183	0.088	1.101	0.541	-6.936	1.519	0.276	-2666.447
2	6.208	1.824	0.186	0.078	1.090	0.538	-6.935	1.520	0.276	-2665.715
3	6.176	1.850	0.187	0.071	1.084	0.537	-6.935	1.521	0.276	-2665.371
4	6.155	1.868	0.188	0.067	1.079	0.536	-6.934	1.521	0.276	-2665.192
5	6.142	1.880	0.189	0.065	1.077	0.535	-6.934	1.521	0.276	-2665.092
6	6.132	1.888	0.189	0.063	1.075	0.534	-6.934	1.522	0.276	-2665.033
7	6.126	1.893	0.189	0.062	1.074	0.534	-6.934	1.522	0.276	-2664.996
8	6.122	1.897	0.190	0.061	1.073	0.534	-6.934	1.522	0.276	-2664.973
9	6.119	1.900	0.190	0.061	1.073	0.534	-6.934	1.522	0.276	-2664.958
10	6.117	1.901	0.190	0.061	1.072	0.534	-6.934	1.522	0.276	-2664.947
11	6.115	1.903	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.941
12	6.114	1.903	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.936
13	6.114	1.904	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.933
14	6.113	1.904	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.931
15	6.113	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.929
16	6.113	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.928
17	6.113	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.928
18	6.113	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.927
19	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.927
20	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.927
21	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
22	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
23	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
24	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
25	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
26	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
27	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926
28	6.112	1.905	0.190	0.060	1.072	0.534	-6.934	1.522	0.276	-2664.926

Table 4: EM iterations results table

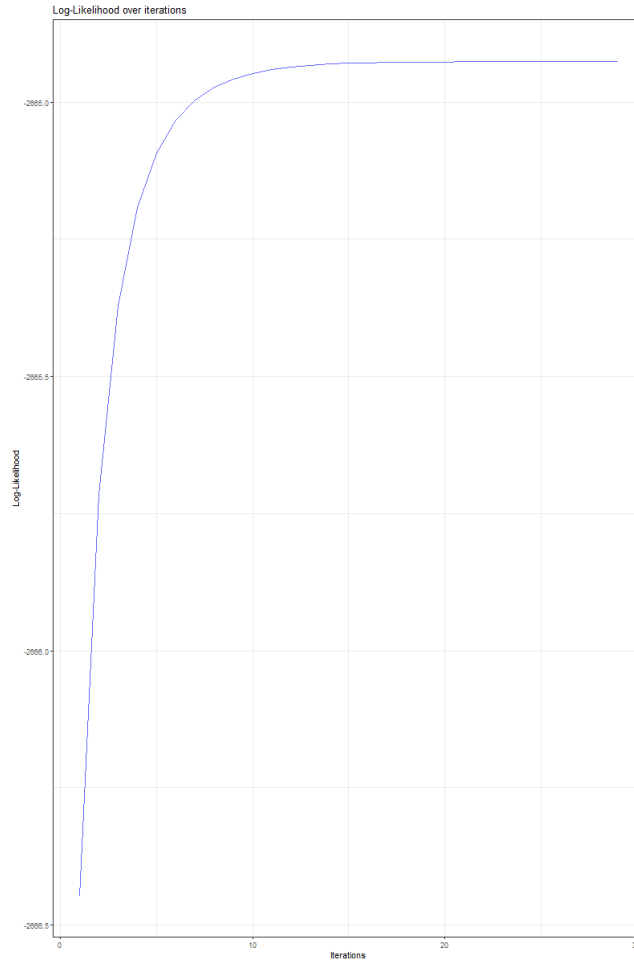


Figure 8: Log-likelihood vs iterations for the execution of the EM algorithm until convergence

#### 5.4 Give the final estimated $\mu_k$ 's, $\sigma_k$ 's and $\pi_k$ 's. How do these compare with the coefficients you chose in the simulation?

The final estimated values compared to the chosen ones are listed in Table 5. The estimated values are very close to the initially chosen values, confirming that the initial assumptions were reasonable. The final log-likelihood value of -2664.926 indicates that the EM algorithm successfully converged to a stable solution. The minor parameter adjustments demonstrate that the algorithm effectively fine-tuned the initial estimates based on the data. The estimated values align closely with the assumed mixture structure, validating the underlying



ing data distribution. Minor shifts in mixing coefficients, means, and standard deviations suggest that while the clusters generally adhered to the expected patterns, some exhibited slightly different densities than initially assumed. The successful convergence of the model indicates that the algorithm reached a local maximum of the likelihood function, further confirming the robustness of the estimation process.

Distribution	Parameter	Chosen Value	Estimated Value
Distribution 1	$\pi_1$	0.200000	0.1901318
	$\mu_1$	6.000000	6.112331
	$\sigma_1$	2.000000	1.905292
Distribution 2	$\pi_2$	0.500000	0.5335142
	$\mu_2$	0.000000	0.05972212
	$\sigma_2$	1.000000	1.071750
Distribution 3	$\pi_3$	0.300000	0.276354
	$\mu_3$	-7.000000	-6.933639
	$\sigma_3$	1.500000	1.521854

Table 5: Chosen vs. estimated parameters

## References

- [1] Jalal Mahmud, Jilin Chen, and Jeffrey Nichols. When will you answer this? estimating response time in twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 7, pages 697–700, 2013.