

Assignment I - CompStat2023

Name of the Team

Team Member A, Team Member B, Team Member C

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1 Montecarlo Simulation II

1.1 Point a)

To prove that the random variable $Y = U^{-\frac{1}{\gamma}}$, where U is Uniform in $(0, 1)$, follows a Pareto distribution, we need to show
Let's begin by finding the cumulative distribution function (CDF) of Y . We have:

$$F_Y(y) = P(Y \leq y) = P\left(U^{-1/\gamma} \leq y\right)$$

Taking the reciprocal of both sides, we get:

$$P\left(\frac{1}{U^{1/\gamma}} \leq \frac{1}{y}\right)$$

Since U follows a standard uniform distribution on the interval $(0, 1)$, the above expression is equivalent to:

$$P\left(U^{1/\gamma} \geq y^{-1}\right) = P\left(U \geq y^{-\gamma}\right)$$

Since U is uniformly distributed, the probability $P(U \geq y^{-\gamma})$ is equal to $1 - P(U < y^{-\gamma})$.
Therefore, the CDF of Y can be written as:

$$F_Y(y) = 1 - P(U < y^{-\gamma})$$

The probability $P(U < y^{-\gamma})$ represents the CDF of a standard uniform distribution evaluated at $y^{-\gamma}$.
Since the CDF of a standard uniform distribution is $F_U(u) = u$ for $0 < u < 1$, we have:

$$F_Y(y) = 1 - y^{-\gamma}$$

Now, let's differentiate the CDF to obtain the PDF of Y :

$$f_Y(y) = \frac{d}{dy}F_Y(y) = \gamma y^{-\gamma-1}$$

Comparing this PDF with the PDF of a Pareto distribution, we can see that they are identical:

$$f_Y(y) = \gamma y^{-\gamma-1} = \gamma x^{-(\gamma+1)}$$

Therefore, we have shown that the random variable $Y = U^{-\frac{1}{\gamma}}$ follows a Pareto distribution with parameter γ .

1.2 point b)

To find the distribution of $Y = \log(X)$, where X follows a Pareto distribution with parameter γ , we need to determine the probability density function (PDF) of Y .

Let's start by expressing the relationship between X and Y using the transformation function:

$$Y = \log(X)$$

To find the PDF of Y , we can use the cumulative distribution function (CDF) method. Let's begin by finding the CDF of Y .

We have:

$$F_Y(y) = P(Y \leq y) = P(\log(X) \leq y)$$

Taking the exponential of both sides, we get:

$$P(X \leq e^y)$$

Since X follows a Pareto distribution, its CDF is given by:

$$F_X(x) = 1 - \left(\frac{1}{x}\right)^\gamma \text{ for } x \geq 1$$

Using the CDF of X , we can express the CDF of Y as follows:

$$F_Y(y) = P(X \leq e^y) = 1 - \left(\frac{1}{e^y}\right)^\gamma = 1 - e^{-\gamma y}$$

To find the PDF of Y , we differentiate the CDF with respect to y :

$$f_Y(y) = \frac{d}{dy} F_Y(y) = \gamma e^{-\gamma y}$$

Therefore, the PDF of Y is given by:

$$f_Y(y) = \gamma e^{-\gamma y}$$

In conclusion, when $Y = \log(X)$ and X follows a Pareto distribution with parameter γ , the resulting distribution of Y is an exponential distribution with parameter γ .

1.3 point c)

```
set.seed(123)

# Function to generate samples from a Pareto distribution
pareto_sampler <- function(n, gamma) {
  u <- runif(n) # Generate n samples from a uniform distribution
  x <- (1/u)^(1/gamma) # Transform the uniform samples to follow a Pareto distribution
  return(x)
}

# Function to generate samples from the logarithmic distribution
logarithmic_sampler <- function(n, gamma) {
  x <- pareto_sampler(n, gamma) # Generate n samples from a Pareto distribution
  y <- log(x) # Transform the Pareto samples to follow a logarithmic distribution
  return(y)
}
```

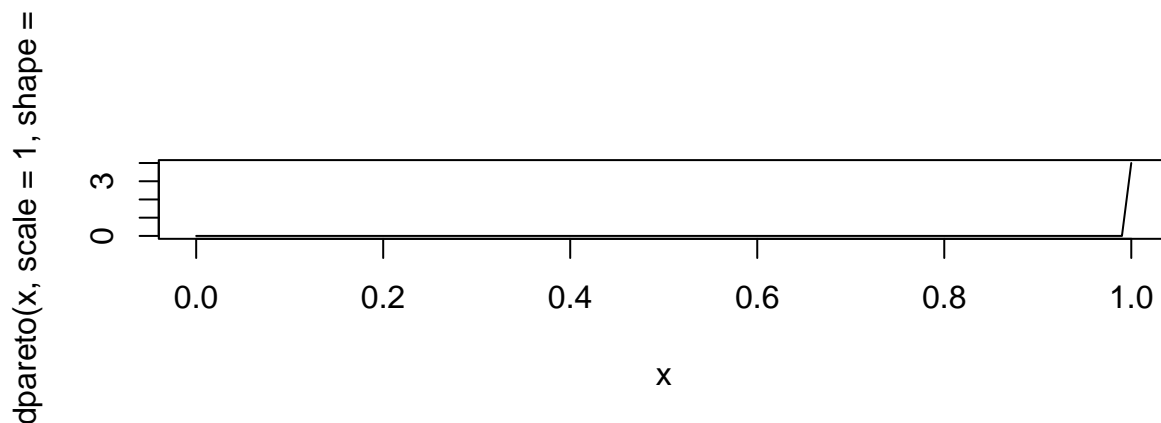
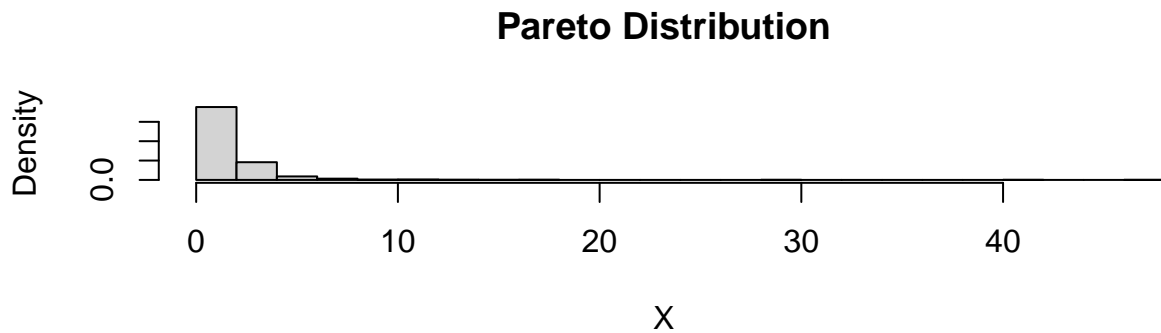
```

# Parameters
n <- 1000 # Number of samples
gamma <- 2 # Parameter of the Pareto distribution

# Generate samples from the Pareto and logarithmic distributions
x_samples <- pareto_sampler(n, gamma)
y_samples <- logarithmic_sampler(n, gamma)

# Plot histograms
par(mfrow = c(2, 1))
hist(x_samples, breaks = 30, main = "Pareto Distribution", xlab = "X", freq = FALSE, xlim = c(0, max(x_
curve(dpareto(x, scale=1, shape = 4))

```

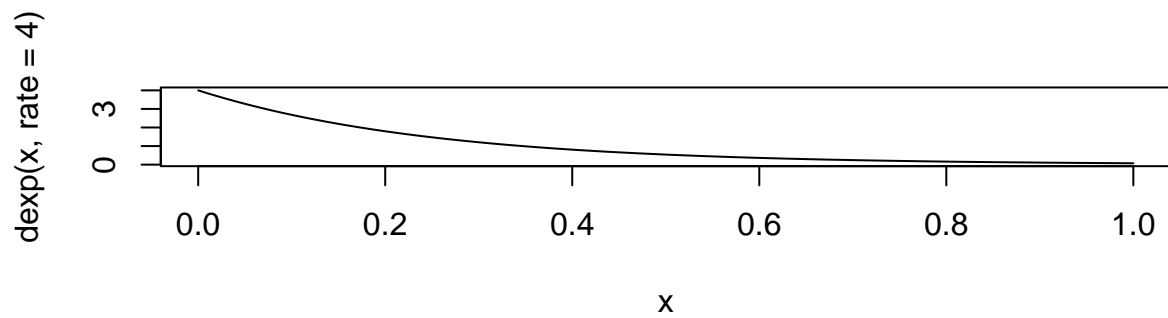
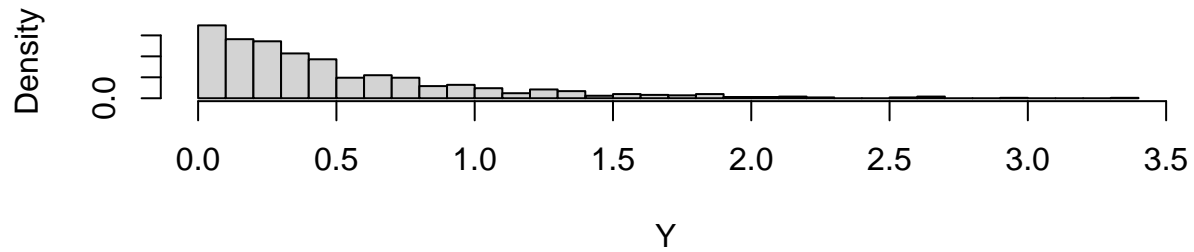


```

hist(y_samples, breaks = 30, main = "Exponential Distribution", xlab = "Y", freq = FALSE, xlim = c(min(
curve(dexp(x, rate=4))

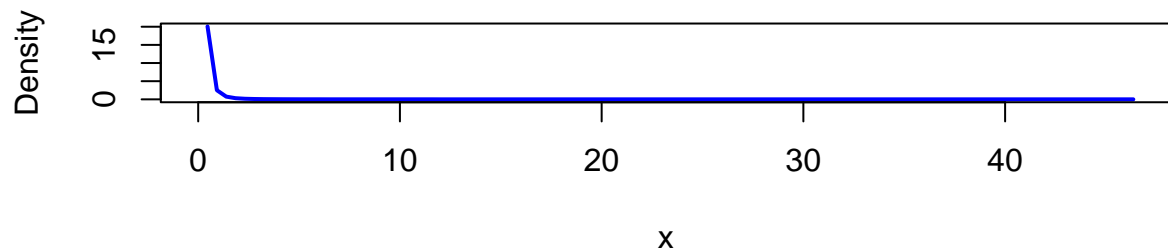
```

Exponential Distribution

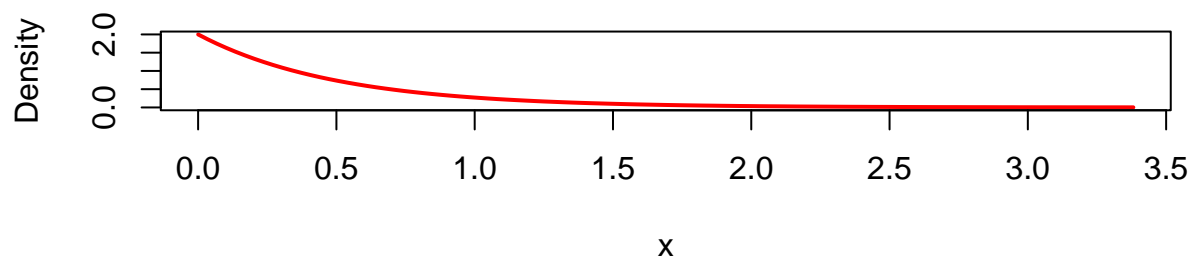


```
# Plot density plots
curve((gamma * x^-(gamma + 1)), from = 0, to = max(x_samples), col = "blue", lwd = 2, ylab = "Density",
curve(dexp(x, gamma), from = min(y_samples), to = max(y_samples), col = "red", lwd = 2, ylab = "Density")
```

Pareto Distribution



Logarithmic Distribution



1.4 point d)

```
# Analytical approach
gamma <- 2 # Pareto parameter
p_analytical <- 1 - (1/5)^gamma

# Monte Carlo estimate
num_samples <- 1000000 # Number of samples
samples <- rpareto(num_samples, scale=1, shape=gamma)
p_mc <- mean(num_samples < 5)

# Output results
p_analytical

## [1] 0.96
p_mc

## [1] 0
```