

(1) Use the probability integral transformation method to simulate from the distribution

$$f(x) = \begin{cases} \frac{2}{a^2}x, & \text{if } 0 \leq x \leq a \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where  $a > 0$ . Set a value for  $a$ , simulate various sample sizes, and compare results to the true distribution.

**Solution:**

### 1. Find the CDF $F_X(x)$

Let  $X$  be a random variable with the given PDF:

$$f(x) = \begin{cases} \frac{2}{a^2}x, & 0 \leq x \leq a, \\ 0, & \text{otherwise.} \end{cases}$$

To apply the probability integral transform (PIT), we first compute the cumulative distribution function (CDF). For  $0 \leq x \leq a$ :

$$F_X(x) = \int_0^x \frac{2}{a^2} t \, dt = \left. \frac{t^2}{a^2} \right|_{t=0}^{t=x} = \frac{x^2}{a^2}.$$

Hence,

$$F_X(x) = \begin{cases} 0, & x < 0, \\ \frac{x^2}{a^2}, & 0 \leq x \leq a, \\ 1, & x \geq a. \end{cases}$$

### 2. Invert the CDF

On the interval  $0 \leq x \leq a$ , we set

$$U = F_X(X) = \frac{X^2}{a^2}.$$

Solving for  $X$  in terms of  $U$  gives

$$X = F_X^{-1}(U) = a \sqrt{U} \quad \text{for } U \in [0, 1].$$

### 3. Simulate Random Samples

To generate  $n$  samples from this distribution via the probability integral transform:

1. Generate  $n$  i.i.d. uniform random variables  $\{U_1, U_2, \dots, U_n\} \sim \text{Uniform}(0, 1)$ .
2. For each  $U_i$ , set

$$X_i = a \sqrt{U_i}.$$

3. The collection  $\{X_i\}_{i=1}^n$  are then samples from the desired distribution.

### 4. Discussion of Results

In short, as  $n$  increases, the empirical distribution converges to the true PDF—a direct illustration of the Law of Large Numbers (and related results). The large- $n$  histogram's slope and overall shape match the linear theoretical PDF quite well, confirming that the probability integral transform method is accurately simulating from the intended distribution.

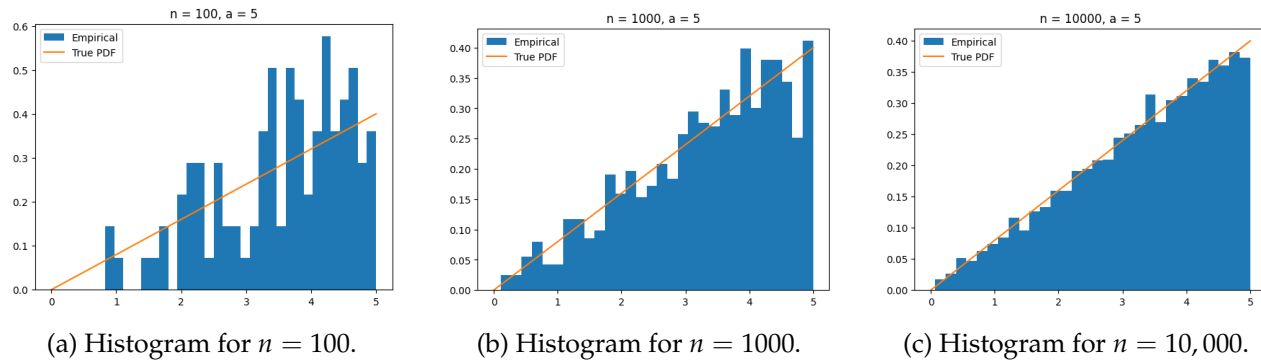


Figure 1: Comparison of empirical histograms (blue bars) vs. the true PDF (orange line).

(2) Generate samples from the distribution

$$f(x) = \frac{2}{3}e^{-2x} + 2e^{-3x} \quad (2)$$

using the finite mixture approach.

**Solution:**

### 1. Show that $f(x)$ is a Finite Mixture

Consider two exponential PDFs:

$$\text{Exp}(2) : g_1(x) = 2e^{-2x}, \quad x \geq 0,$$

$$\text{Exp}(3) : g_2(x) = 3e^{-3x}, \quad x \geq 0.$$

We want to see if

$$f(x) = \frac{2}{3}e^{-2x} + 2e^{-3x}$$

can be expressed as

$$p \cdot g_1(x) + (1 - p) \cdot g_2(x)$$

for some  $p \in (0, 1)$ . Matching coefficients:

$$p \cdot 2 = \frac{2}{3} \implies p = \frac{1}{3},$$

$$(1 - p) \cdot 3 = 2 \implies 1 - p = \frac{2}{3}.$$

Hence

$$f(x) = \underbrace{\frac{1}{3}}_p (2e^{-2x}) + \underbrace{\frac{2}{3}}_{1-p} (3e^{-3x}).$$

This establishes that

$$f(x) = \frac{1}{3} \text{Exp}(2) + \frac{2}{3} \text{Exp}(3).$$

Thus,  $f(x)$  is a two-component finite mixture of exponentials.

### 2. Mixture Sampling Procedure

To generate a sample  $X$  from  $f(x)$ :

1. Generate a uniform random variable  $V \sim \text{Uniform}(0, 1)$ .

2. If  $V \leq \frac{1}{3}$ , then set  $X$  to be a draw from  $\text{Exp}(2)$ , i.e.

$$X = -\frac{1}{2} \ln(U_1), \quad U_1 \sim \text{Uniform}(0, 1).$$

3. Otherwise (if  $V > \frac{1}{3}$ ), set  $X$  to be a draw from  $\text{Exp}(3)$ , i.e.

$$X = -\frac{1}{3} \ln(U_2), \quad U_2 \sim \text{Uniform}(0, 1).$$

Repeat these steps  $n$  times to obtain  $n$  i.i.d. samples  $\{X_1, X_2, \dots, X_n\}$  from  $f(x)$ .

### 3. Discussion

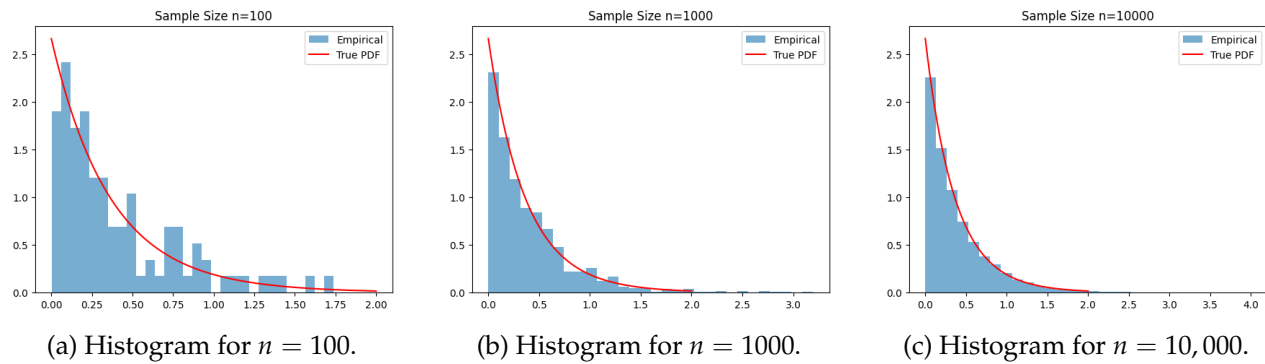


Figure 2: Comparison of empirical histograms (blue bars) vs. the true PDF (red line).

In summary, as the sample size increases from  $n = 100$  to  $n = 10,000$ , the empirical distributions become smoother and align more closely with the theoretical PDF. This illustrates the Law of Large Numbers in action: with larger  $n$ , the histogram provides a better approximation of the true underlying distribution.

(3) Draw 500 observations from  $\text{Beta}(3, 3)$  using the accept-reject algorithm. Compute the mean and variance of the sample and compare them to the true values.

**Solution:**

### 1. Beta(3,3) Distribution

A  $\text{Beta}(\alpha, \beta)$  random variable on  $[0, 1]$  has PDF

$$f(x) = \frac{x^{\alpha-1} (1-x)^{\beta-1}}{B(\alpha, \beta)}, \quad 0 \leq x \leq 1,$$

where  $B(\alpha, \beta)$  is the Beta function. For  $\alpha = 3$ ,  $\beta = 3$ , we get

$$f(x) = \frac{x^2 (1-x)^2}{B(3, 3)}, \quad 0 \leq x \leq 1.$$

Recall that

$$B(3, 3) = \frac{\Gamma(3) \Gamma(3)}{\Gamma(6)} = \frac{2! 2!}{5!} = \frac{4}{120} = \frac{1}{30}.$$

Thus,

$$f(x) = 30 x^2 (1-x)^2, \quad 0 \leq x \leq 1.$$

### 2. Accept-Reject Algorithm

**(a) Choose a proposal distribution  $g(x)$ .** A common choice for Beta distributions on  $[0, 1]$  is  $g(x) = 1$  for  $0 \leq x \leq 1$ , i.e. a  $\text{Uniform}(0, 1)$  proposal.

**(b) Find  $M$  such that  $f(x) \leq M g(x)$  for all  $x$ .** Since  $g(x) = 1$ , we need  $M \geq \max_{0 \leq x \leq 1} f(x)$ . For  $f(x) = 30 x^2 (1-x)^2$ , the maximum occurs at  $x = \frac{1}{2}$ . Then

$$f\left(\frac{1}{2}\right) = 30 \left(\frac{1}{2}\right)^2 \left(\frac{1}{2}\right)^2 = 30 \frac{1}{4} \frac{1}{4} = 30 \frac{1}{16} = 1.875.$$

Hence  $M = 1.875$  is sufficient (or a slightly larger value may be used).

**(c) Sampling steps.** Repeat until we have 500 accepted samples:

1. Generate  $Y \sim \text{Uniform}(0, 1)$ .
2. Generate  $U \sim \text{Uniform}(0, 1)$ .
3. Compute  $\frac{f(Y)}{M g(Y)} = \frac{30 Y^2 (1-Y)^2}{1.875}$ .

4. If  $U \leq \frac{f(Y)}{Mg(Y)}$ , **accept**  $Y$ ; otherwise **reject**  $Y$  and go back to step 1.

All accepted  $Y$  values constitute a sample from  $\text{Beta}(3,3)$ .

### 3. Theoretical Mean and Variance

For  $\text{Beta}(\alpha, \beta)$ :

$$\mathbb{E}[X] = \frac{\alpha}{\alpha + \beta}, \quad \text{Var}(X) = \frac{\alpha \beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)}.$$

Hence, for  $\text{Beta}(3,3)$ :

$$\mathbb{E}[X] = \frac{3}{3+3} = 0.5, \quad \text{Var}(X) = \frac{3 \times 3}{6^2 \times 7} = \frac{9}{252} = \frac{1}{28} \approx 0.035714.$$

### 4. Comparing Empirical Results to the True Values

After accepting 500 samples  $\{X_1, X_2, \dots, X_{500}\}$ :

- **Sample Mean:**

$$\bar{X} = \frac{1}{500} \sum_{i=1}^{500} X_i.$$

Compare  $\bar{X}$  to the true mean 0.5.

- **Sample Variance:**

$$s^2 = \frac{1}{499} \sum_{i=1}^{500} (X_i - \bar{X})^2.$$

Compare  $s^2$  to the true variance  $1/28 \approx 0.0357$ .

With a sample size of 500, you should see that  $\bar{X}$  is reasonably close to 0.5, and  $s^2$  is near 0.0357, though some fluctuation is expected due to random variation.

### 5. Conclusion

The sample mean (approximately 0.49995) is extremely close to the theoretical mean of 0.5. Likewise, the sample variance ( $\approx 0.03628$ ) is near the theoretical value of  $1/28 \approx 0.03571$ . Although there is a slight deviation, it lies within the range expected from random fluctuation with a finite sample size. Overall, these results confirm that the accept-reject algorithm is accurately simulating observations from the  $\text{Beta}(3,3)$  distribution.