

# Module Experiment 3F3

## Random variables and random number generation

Tahmid Azam  
Emmanuel College

November 2025

Code is available at <https://github.com/tahmidazam/3f3-lab>.

# 1 Uniform and normal random variables

## 1.1 Estimating a probability density function

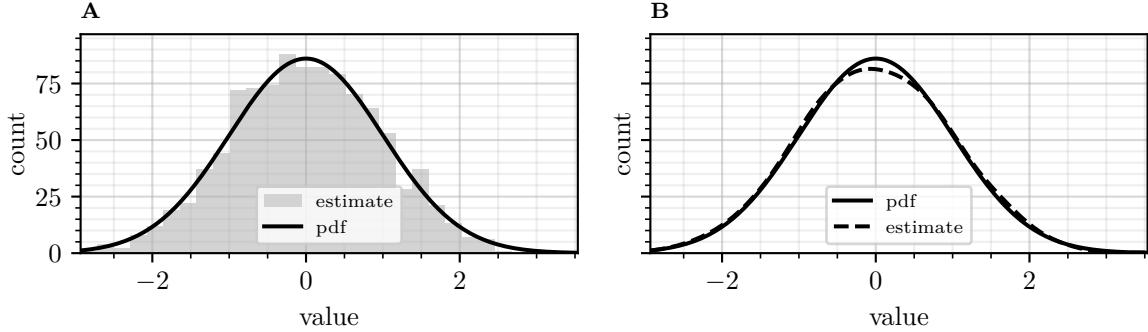


Figure 1: Histogram (subplot A, bin count,  $k = 30$ ) and kernel smooth density function (subplot B,  $\mathcal{K} = \mathcal{N}(x|0, 1)$ ,  $\sigma = 0.3$ ) estimates of random samples from a normal distribution (`numpy.random.randn`,  $n = 1000$ ) compared to the exact scaled probability density function (pdf) of a normal distribution (`scipy.stats.norm`).

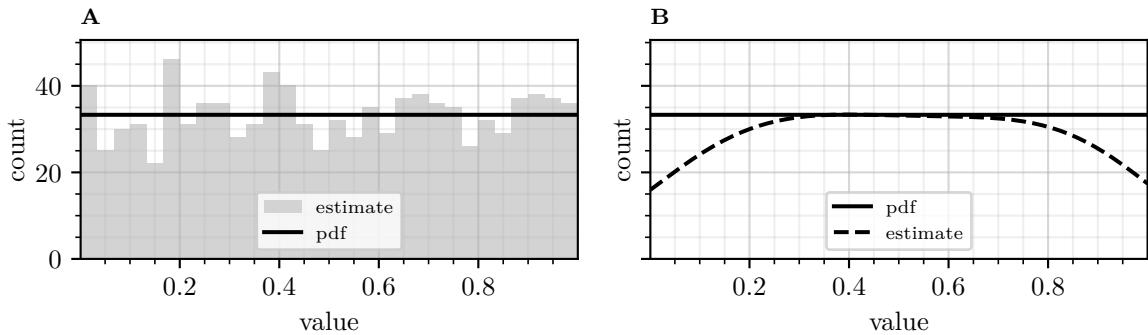


Figure 2: Histogram (subplot A,  $k = 30$ ) and kernel smooth density function (subplot B,  $\mathcal{K} = \mathcal{N}(x|0, 1)$ ,  $\sigma = 0.15$ ) estimates of random samples from a uniform distribution (`numpy.random.rand`,  $n = 1000$ ) compared to the exact scaled pdf of a uniform distribution (`scipy.stats.uniform`).

The kernel density estimate (KDE) produces a continuous and smooth function, unlike the discontinuous histogram. Both methods require selection of a resolution parameter (width,  $\sigma$ , for the KDE; bin count for the histogram). If these are too small, this leads to overfitting to the random samples; too large loses detail. The KDE also requires selection of a kernel function. The KDE performs poorly near the sharp edges of the uniform distribution (Figure 2) and creates artificial tails outside its domain of  $[0, 1]$  if evaluated there. The complexity of the histogram method for  $n$  is  $\mathcal{O}(n)$  (i.e., bin assignment for each  $n$ ); for evaluating the KDE for  $m$  points, the complexity is  $\mathcal{O}(n \times m)$  (i.e., sum over  $n$  kernels for each data point  $m$ ) [1]. Optimised implementations of the KDE using the fast fourier transform achieve  $\mathcal{O}(n + m \log m)$  [2]. Regardless, the KDE is more computationally expensive than the histogram method.

```

from typing import Callable

import numpy as np
from matplotlib import pyplot as plt

from constants import PAGE_WIDTH_IN_INCHES
from ksdensity import ksdensity
from save_fig import save_fig

def plot_pdf_and_estimate(
    plot_id: str,
    gen_fn: Callable[[int], np.ndarray],
    pdf: Callable[[np.ndarray], np.ndarray],
    ks_density_width: float = 0.3,
    n: int = 1_000,
    bin_count: int = 30,
    linspace_num: int = 1_000,
):
    """
    Plots the histogram estimate and KDE of a given distribution.

    :param plot_id: The id of the plot used to name the exported file.
    :param gen_fn: The function used to generate samples.
    :param pdf: The probability density function.
    :param ks_density_width: The width used for the KDE.
    :param n: The number of samples.
    :param bin_count: The number of histogram bins.
    :param linspace_num: The number of points to evaluate the KDE at.
    """
    samples = gen_fn(n)
    samples_min = np.min(samples)
    samples_max = np.max(samples)
    x = np.linspace(samples_min, samples_max, linspace_num)
    pdf_values = pdf(x)
    ks_density = ksdensity(samples, width=ks_density_width)

    fig, (hist_ax, ksd_ax) = plt.subplots(
        figsize=(PAGE_WIDTH_IN_INCHES, 2),
        ncols=2,
        nrows=1,
        sharey=True
    )
    counts, bin_edges, _ = hist_ax.hist(
        samples,
        bins=bin_count,
        color="lightgrey",
        label="estimate"
    )

    bin_width = bin_edges[1] - bin_edges[0]
    scaled_pdf = pdf_values * bin_width * n
    scaled_ksd = ks_density * bin_width * n

    hist_ax.plot(x, scaled_pdf, label="pdf", color="black")
    ksd_ax.plot(x, scaled_pdf, label="pdf", color="black")
    ksd_ax.plot(x, scaled_ksd, label="estimate", color="black", linestyle="dashed")

    ylim = np.max(counts) * 1.1

    for ax in [hist_ax, ksd_ax]:
        ax.set_xlim(left=samples_min, right=samples_max)
        ax.set_xlabel("value")
        ax.set_ylabel("count")
        ax.legend(fontsize="x-small", loc="lower center")

    hist_ax.set_title("A", fontsize="small", loc="left", fontweight="bold")
    ksd_ax.set_title("B", fontsize="small", loc="left", fontweight="bold")

    save_fig(question=1, name=plot_id)

```

Figure 3: Python function definition for plotting the histogram estimate and KDE in Figure 1 and Figure 2.

```

plot_pdf_and_estimate(
    plot_id="normal",
    gen_fn=np.random.randn,
    pdf=lambda x: norm.pdf(x, 0, 1)
)

plot_pdf_and_estimate(
    plot_id="uniform",
    gen_fn=np.random.rand,
    pdf=lambda x: uniform.pdf(x, 0, 1),
    ks_density_width=0.15
)

```

Figure 4: Python function calls for plotting the histogram estimate and KDE in Figure 1 and Figure 2.

## 1.2 The multinomial distribution

For a continuous uniform distribution over  $[a, b]$ , we divide the interval into  $k$  equal-width bins. The probability of a random sample (of total  $N$  samples) falling into bin  $j$  is given by  $p_j = \frac{1}{k}$ , where  $j = 1, 2, \dots, k$ . Using the multinomial theory, we can derive the theoretical mean and standard deviation of the histogram data as a function of  $N$ :

$$E[X_j] = Np_j = \frac{N}{k} \quad (1)$$

$$\text{Var}(X_j) = Np_j(1 - p_j) = N \frac{1}{k} \left(1 - \frac{1}{k}\right) = \frac{N(k-1)}{k^2} \quad (2)$$

$$\sigma_{X_j} = \sqrt{\frac{N(k-1)}{k}} \quad (3)$$

Note the mean does not depend on  $N$ . To obtain the histogram estimate from the counts, we divide  $X_j$  by the number of samples  $N$ . Thus, we can derive expected value for the histogram estimate:

$$E\left[\frac{X_j}{N}\right] = \frac{1}{k} = p_j \quad (4)$$

Using the property  $\text{Var}(aX) = a^2\text{Var}(X)$ , we can derive the variance for the histogram estimate:

$$\text{Var}\left(\frac{X_j}{N}\right) = \frac{1}{N^2} \text{Var}(X_j) = \frac{1}{N^2} \cdot \frac{N(k-1)}{k^2} = \frac{k-1}{Nk^2} \quad (5)$$

$$\lim_{N \rightarrow \infty} \text{Var}\left(\frac{X_j}{N}\right) = \lim_{N \rightarrow \infty} \frac{k-1}{Nk^2} = 0 \quad (6)$$

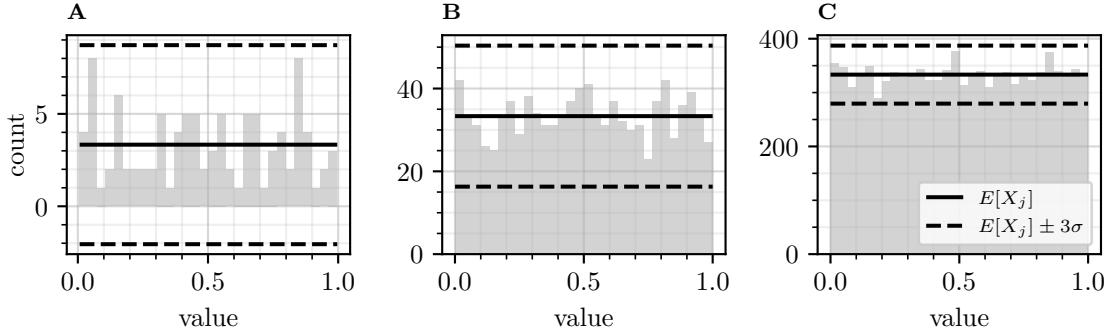


Figure 5: Data histograms ( $k = 30$ ) for  $N = 10^2$  (subplot A),  $N = 10^3$  (subplot B), and  $N = 10^4$  (subplot C) random samples from a uniform distribution (`numpy.random.rand`).

As  $N$  becomes large, the variance approaches 0 and the mean remains fixed at the true probability  $p_j = \frac{1}{k}$ . Consequently, the histogram estimate converges to the true pdf of the uniform distribution. In

Figure 5, the histogram counts fluctuate around the theoretical mean, and the majority of bins lie within  $[E[X_j] - 3\sigma, E[X_j] + 3\sigma]$ . As  $N$  increases, the fluctuations decrease and the histogram approaches the true pdf of the uniform distribution, consistent with the multinomial distribution theory. This consolidates the accuracy of Python's uniformly distributed random variates.

```

import numpy as np
from matplotlib import pyplot as plt

from constants import PAGE_WIDTH_IN_INCHES
from save_fig import save_fig

def plot_multinomial_theory(
    n_values: list[int],
    subplot_titles: list[str],
    k: int = 30,
) -> None:
    """
    Plots histograms of the uniform distribution with overlaid horizontal
    lines for the theoretical mean and -3 and 3 times the standard deviation.

    :param n_values: The values for the sample count for each subplot.
    :param subplot_titles: The titles for each subplot.
    :param k: The number of histogram bins.
    """
    fig, axes = plt.subplots(figsize=(PAGE_WIDTH_IN_INCHES, 2), ncols=len(n_values), nrows=1)

    for i, (ax, n) in enumerate(zip(axes, n_values)):
        vector = np.random.rand(n)
        p = 1 / k
        theoretical_mean = n * p
        theoretical_std_dev = np.sqrt(n * p * (1 - p))
        counts, bin_edges, _ = ax.hist(vector, bins=k, color="lightgrey")

        ax.hlines(
            theoretical_mean, bin_edges[0], bin_edges[-1],
            color="black",
            label=f"${E[X_j]}$",
        )

        three_std_dev_lines = [
            theoretical_mean + 3 * theoretical_std_dev,
            theoretical_mean - 3 * theoretical_std_dev
        ]
        ax.hlines(
            three_std_dev_lines,
            bin_edges[0], bin_edges[-1],
            color="black",
            linestyle="dashed",
            label=r"${E[X_j]} \pm 3\sigma$"
        )

        ax.set_xlabel("value")
        ax.set_title(subplot_titles[i], fontsize="small", loc="left", fontweight="bold")

    axes[0].set_ylabel("count")
    axes[-1].legend(fontsize="x-small", loc="lower right")

    save_fig(question=1, name="uniform_multinomial")

```

Figure 6: Python function implementation for plotting the histograms in Figure 5.

```

plot_multinomial_theory(
    n_values=[100, 1_000, 10_000],
    subplot_titles=["A", "B", "C"],
)

```

Figure 7: Python function calls for plotting the histograms in Figure 5.

## 2 Functions of random variables

For  $p_X(x) = \mathcal{N}(x|0, 1)$ , and  $y = f(x) = ax + b$  (Figure 8, subplot A), we can derive  $p_Y(y)$  using the Jacobian formula:

$$p_X(x) = \frac{1}{\sqrt{2\pi}\sigma^2} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right] \Bigg|_{\mu=0, \sigma^2=1} = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{x^2}{2}\right] \quad (7)$$

$$\frac{dy}{dx} = a \quad (8)$$

$$f^{-1}(y) = \frac{y-b}{a} \quad (9)$$

$$p_Y(y) = p_X(x) \frac{1}{\left|\frac{dy}{dx}\right|} \Bigg|_{x=f^{-1}(y)} = p_X\left(\frac{y-b}{a}\right) \cdot \frac{1}{|a|} = \frac{1}{|a|\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{y-b}{a}\right)^2\right] \quad (10)$$

$$= \frac{1}{\sqrt{2\pi a^2}} \exp\left[-\frac{(y-b)^2}{2a^2}\right] = \mathcal{N}(y|b, a^2) \quad (11)$$

For the case  $y = f(x) = x^2$  (Figure 8, subplot B), we have to account for a 2-to-1 mapping:

$$\frac{dy}{dx} = 2x \quad (12)$$

$$f^{-1}(y) = \pm\sqrt{y}, \quad y \geq 0 \quad (13)$$

$$p_Y(y) = p_X(x) \frac{1}{\left|\frac{dy}{dx}\right|} \Bigg|_{x=\sqrt{y}} + p_X(x) \frac{1}{\left|\frac{dy}{dx}\right|} \Bigg|_{x=-\sqrt{y}} = \frac{p_X(\sqrt{y})}{2\sqrt{y}} + \frac{p_X(-\sqrt{y})}{2\sqrt{y}} \quad (14)$$

$$= \frac{1}{\sqrt{2\pi y}} \exp\left[-\frac{y}{2}\right], \quad y \geq 0 \quad (15)$$

Thus, squaring a standard normal random variable yields a distribution supported on  $y \geq 0$ , corresponding to a chi-squared distribution with one degree of freedom.

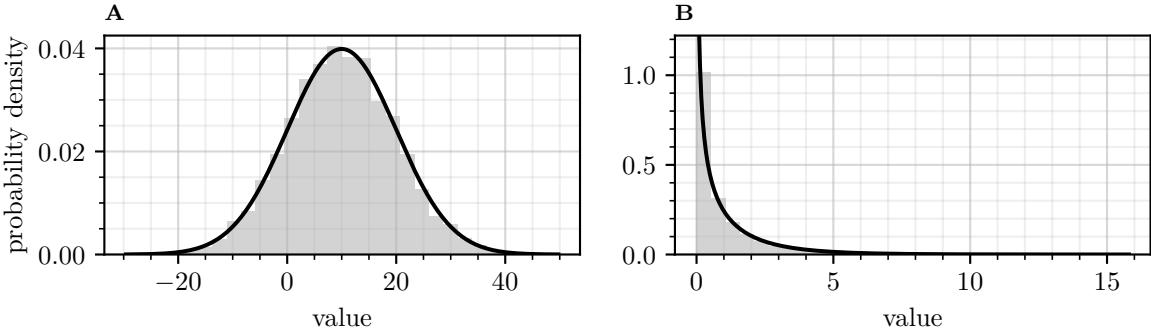


Figure 8: Histogram ( $k = 30$ ) of  $N = 10^5$  samples  $x^{(i)}$  to give  $y^{(i)} = f(x^{(i)})$  using  $f(x) = ax + b$  (subplot A,  $a = b = 10$ ) and  $f(x) = x^2$  (subplot B) overlaid with the theoretical pdf calculated using the Jacobian.

```

import numpy as np
from matplotlib import pyplot as plt
from scipy.stats import norm

from constants import PAGE_WIDTH_IN_INCHES
from save_fig import save_fig

def jacobian(
    a: float = 10,
    b: float = 10,
    n: int = 10_000,
    bin_count: int = 30,
    linspace_num: int = 1_000,
):
    """
    Plots histograms of linear [f(x) = ax + b] and square [f(x) = x^2] transformations of
    samples from the normal distribution, overlaid with the theoretical pdfs calculated
    using the Jacobian.

    :param a: The value of constant a.
    :param b: The value of constant b.
    :param n: The number of samples taken from the normal distribution.
    :param bin_count: The number of histogram bins.
    :param linspace_num: The number of points to evaluate the pdfs at.
    """

    x = np.random.randn(n)
    y_linear = a * x + b
    y_square = x ** 2
    y_linear_vals = np.linspace(min(y_linear), max(y_linear), num=linspace_num)
    y_square_vals = np.linspace(
        start=1e-6, # Avoid division by 0
        stop=max(y_square),
        num=linspace_num
    )
    p_y_linear = (1 / abs(a)) * norm.pdf((y_linear_vals - b) / a)
    p_y_square = np.array([
        0.5 / np.sqrt(val) * (norm.pdf(np.sqrt(val)) + norm.pdf(-np.sqrt(val)))
        for val in y_square_vals
    ])

    fig, (linear_ax, square_ax) = plt.subplots(
        nrows=1,
        ncols=2,
        figsize=(PAGE_WIDTH_IN_INCHES, 2)
    )

    linear_ax.hist(y_linear, bins=bin_count, color="lightgrey", density=True)
    linear_ax.plot(y_linear_vals, p_y_linear, color="black")
    counts_square, _, _ = square_ax.hist(y_square, bins=bin_count, color="lightgrey", density=True)
    square_ax.plot(y_square_vals, p_y_square, color="black")

    max_bin_count = counts_square.max()
    square_ax.set_ylim(top=1.2 * max_bin_count) # Limit y-axis due to large values close to 0.
    linear_ax.set_xlabel("value")
    square_ax.set_xlabel("value")
    linear_ax.set_ylabel("probability density")
    linear_ax.set_title("A", fontsize="small", loc="left", fontweight="bold")
    square_ax.set_title("B", fontsize="small", loc="left", fontweight="bold")

    save_fig(question=2, name="jacobian")

```

Figure 9: Python implementation for plotting the histogram estimates in Figure 8.

### 3 Inverse cumulative distribution function method

For the exponential distribution with mean 1 with pdf  $p(y) = \exp(-y)$ ,  $y \geq 0$ , we can derive the cumulative distribution function (CDF) and its inverse:

$$F_Y(y) = P(Y \leq y) = \int_0^y e^{-t} dt = [-e^{-t}]_0^y = 1 - e^{-y}, \quad y \geq 0 \quad (16)$$

$$F_Y^{-1}(u) = -\ln(1 - u), \quad u \in [0, 1] \quad (17)$$

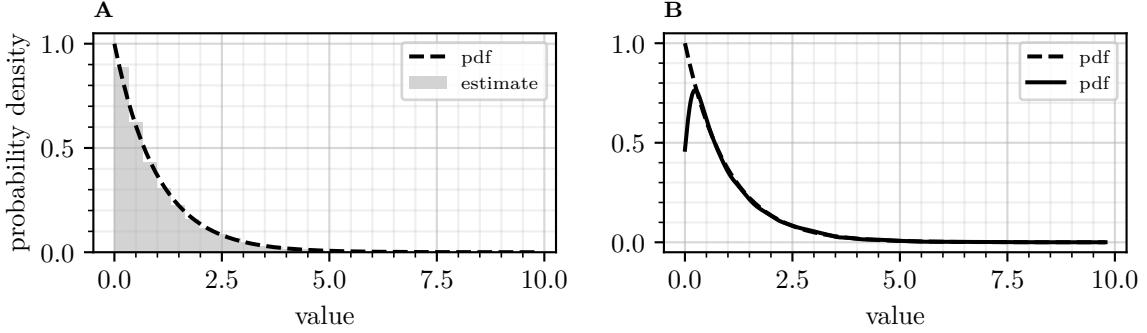


Figure 10: Histogram (subplot A,  $k = 30$ ) and kernel density (subplot B,  $\mathcal{K} = \mathcal{N}(x|0, 1)$ ,  $\sigma = 0.15$ ) estimates from  $N = 10^4$  samples generated using the inverse CDF method compared to the exact pdf of the exponential distribution with mean 1.

```

import numpy as np
from matplotlib import pyplot as plt

from constants import PAGE_WIDTH_IN_INCHES
from ksdensity import ksdensity
from save_fig import save_fig

def inverse_cdf(
    ks_density_width: float = 0.15,
    n: int = 10_000,
    k: int = 30,
    linspace_num: int = 1_000,
):
    """
    Plots the histogram estimate and the KDE for the exponential
    distribution with mean 1 using the inverse cdf method.

    :param ks_density_width: The width used in the KDE.
    :param n: The number of samples from the uniform distribution.
    :param k: The number of histogram bins.
    :param linspace_num: The number of points to evaluate the KDE at.
    """

    u_samples = np.random.rand(n)
    exp_samples = -np.log(1 - u_samples)
    x = np.linspace(
        start=exp_samples.min(),
        stop=exp_samples.max(),
        num=linspace_num
    )
    pdf = np.exp(-x)
    ks_density = ksdensity(exp_samples, width=ks_density_width)

    fig, (hist_ax, ksd_ax) = plt.subplots(figsize=(PAGE_WIDTH_IN_INCHES, 2), nrows=1, ncols=2)

    hist_ax.plot(x, pdf, color="black", linestyle="dashed", label="pdf")
    ksd_ax.plot(x, pdf, color="black", linestyle="dashed", label="pdf")
    hist_ax.hist(exp_samples, bins=k, color="lightgrey", density=True, label="estimate")
    ksd_ax.plot(x, ks_density(x), color="black", label="pdf")

    hist_ax.set_ylabel("probability density")
    hist_ax.set_title("A", fontsize="small", loc="left", fontweight="bold")
    ksd_ax.set_title("B", fontsize="small", loc="left", fontweight="bold")

    for ax in [hist_ax, ksd_ax]:
        ax.legend(fontsize="x-small")
        ax.set_xlabel("value")

    save_fig(question=3, name="inverse_cdf")

```

Figure 11: Python implementation for plotting the histogram and KDE estimates in Figure 10.

## 4 Simulation from a ‘difficult’ density

For  $\alpha \in (0, 2)$  ( $\alpha \neq 1$ ),  $\beta \in [-1, 1]$ , let:

$$b = \frac{1}{\alpha} \arctan \left[ \beta \tan \left( \frac{\pi \alpha}{2} \right) \right] \quad (18)$$

$$s = \left[ 1 + \beta^2 \tan^2 \left( \frac{\pi \alpha}{2} \right) \right]^{\frac{1}{2\alpha}} \quad (19)$$

$$U \sim \mathcal{U}\left(-\frac{\pi}{2}, \frac{\pi}{2}\right) \quad (20)$$

$$V \sim \mathcal{E}(V|1) \quad (21)$$

$$X = s \frac{\sin(\alpha(U+b))}{(\cos(U))^{\frac{1}{\alpha}}} \left( \frac{\cos(U-\alpha(U+b))}{V} \right)^{\frac{1-\alpha}{\alpha}} \quad (22)$$

In Figure 12, varying  $\alpha$  changes the width of the density and varying  $\beta$  shifts the mass left or right. The parameter  $\alpha \in (0, 2)$  controls the spread of the distribution. Small values of  $\alpha$  concentrate most

of the probability mass near the center, producing a sharp peak, while larger values of  $\alpha$  spread the distribution and increase the relative probability of extreme values. The parameter  $\beta \in [-1, 1]$  controls the skewness:  $\beta = 0$  gives a symmetric distribution,  $\beta > 0$  skews it to the right, and  $\beta < 0$  skews it to the left.

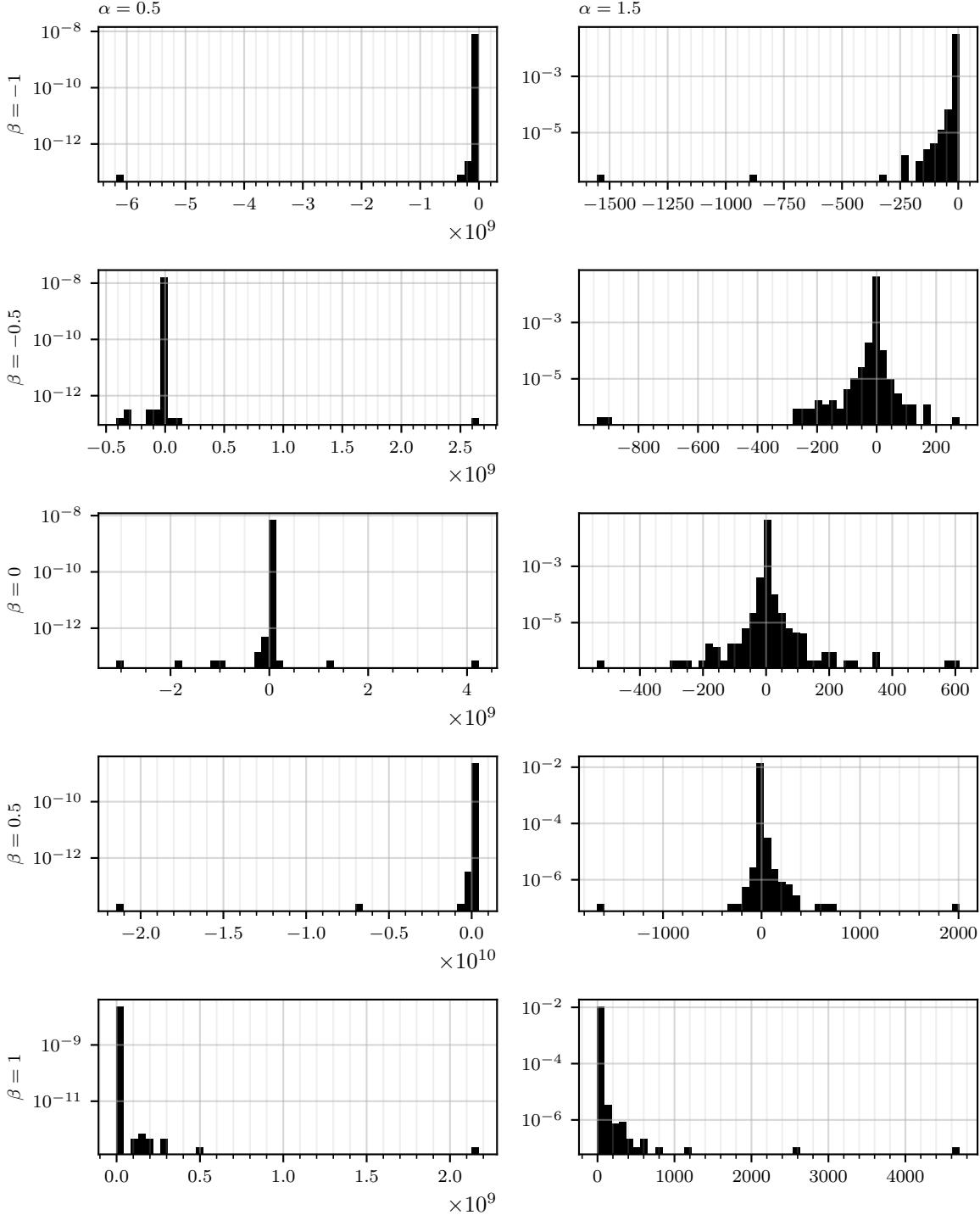


Figure 12: Histogram density estimates ( $k = 30, \alpha = 0.5, 1.5, \beta = -1, -0.5, 0, 0.5, 1$ ) from  $N = 10^5$  samples from  $X$ .

```

import numpy as np

def calc_const_s(alpha: float, beta: float) -> float:
    return np.power(
        1 + np.power(beta, 2) * np.power(np.tan(np.pi * alpha / 2), 2),
        1 / (2 * alpha)
    )

```

Figure 13: Python implementation for calculating  $s$ .

```

import numpy as np

def calc_const_b(alpha: float, beta: float) -> float:
    return (1 / alpha) * np.arctan(beta * np.tan(np.pi * alpha / 2))

```

Figure 14: Python implementation for calculating  $b$ .

```

import numpy as np

def calc_rv_x(
    alpha: float,
    s: float,
    b: float,
    u: np.ndarray,
    v: np.ndarray
) -> np.ndarray:
    return s * ((np.sin(alpha * (u + b))) / (np.power(
        np.cos(u),
        1 / alpha
    ))) * np.power(
        ((np.cos(u - alpha * (u + b))) / (v)),
        (1 - alpha) / alpha
    )

```

Figure 15: Python implementation for calculating the random variable  $X$ .

```

import numpy as np
from matplotlib import pyplot as plt

from calc_const_b import calc_const_b
from calc_const_s import calc_const_s
from calc_rv_x import calc_rv_x
from constants import PAGE_WIDTH_IN_INCHES, PAGE_HEIGHT_IN_INCHES
from save_fig import save_fig


def simulation(
    alphas: list[float],
    betas: list[float],
    n: int = 100_000,
    k: int = 50,
) -> None:
    """
    Plots histogram density estimates for a set of alpha and beta values.

    :param alphas: The list of alpha values, where 0 <= alpha <= 2, alpha != 1.
    :param betas: The list of beta values, where beta -1 <= beta <= 1.
    :param n: The number of samples of X to plot.
    :param k: The number of histogram bins.
    """
    fig, axes = plt.subplots(
        nrows=len(betas),
        ncols=len(alphas),
        figsize=(PAGE_WIDTH_IN_INCHES, PAGE_HEIGHT_IN_INCHES * 0.8),
    )

    for i, beta in enumerate(betas):
        for j, alpha in enumerate(alphas):
            b = calc_const_b(alpha, beta)
            s = calc_const_s(alpha, beta)
            u = np.random.uniform(-np.pi / 2, np.pi / 2, size=n)
            v = np.random.exponential(scale=1, size=n)
            x = calc_rv_x(alpha, s, b, u, v)

            ax = axes[i, j]
            ax.tick_params(axis='both', which='major', labelsize="small")
            ax.hist(x, bins=k, label="histogram", color="black", density=True, log=True)

            if j == 0:
                ax.set_ylabel(rf"\beta = {beta}", fontsize="small")

            if i == 0:
                ax.set_title(rf"\alpha = {alpha}", fontsize="small", loc="left")

    save_fig(question=4, name="simulation")

```

Figure 16: Python implementation for plotting the histogram estimates in Figure 12.

## References

- [1] Vikas C. Raykar, Ramani Duraiswami, and Linda H. Zhao. “Fast Computation of Kernel Estimators”. In: *Journal of Computational and Graphical Statistics* 19.1 (Jan. 1, 2010), pp. 205–220. ISSN: 1061-8600. DOI: 10.1198/jcgs.2010.09046. URL: <https://doi.org/10.1198/jcgs.2010.09046> (visited on 11/08/2025).
- [2] Jeffrey Heer. “Fast & Accurate Gaussian Kernel Density Estimation”. In: *2021 IEEE Visualization Conference (VIS)*. 2021 IEEE Visualization Conference (VIS). Oct. 2021, pp. 11–15. DOI: 10.1109/VIS49827.2021.9623323. URL: <https://ieeexplore.ieee.org/document/9623323> (visited on 11/08/2025).