

---

## ENGINEERING TRIPPOS PART IIA

EIETL

MODULE EXPERIMENT 3F3

### RANDOM VARIABLES and RANDOM NUMBER GENERATION Short Report

Name: Yongqing Jiang

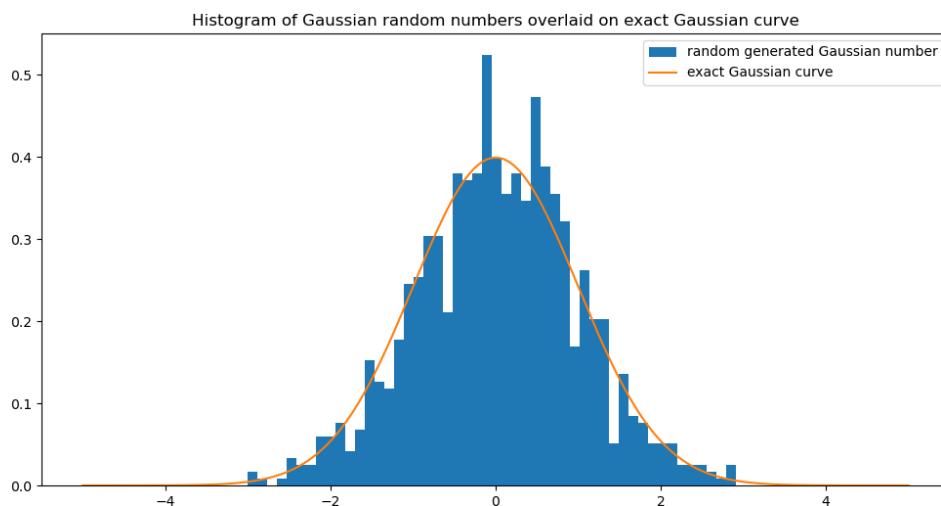
College: Peterhouse

crsid: yj375

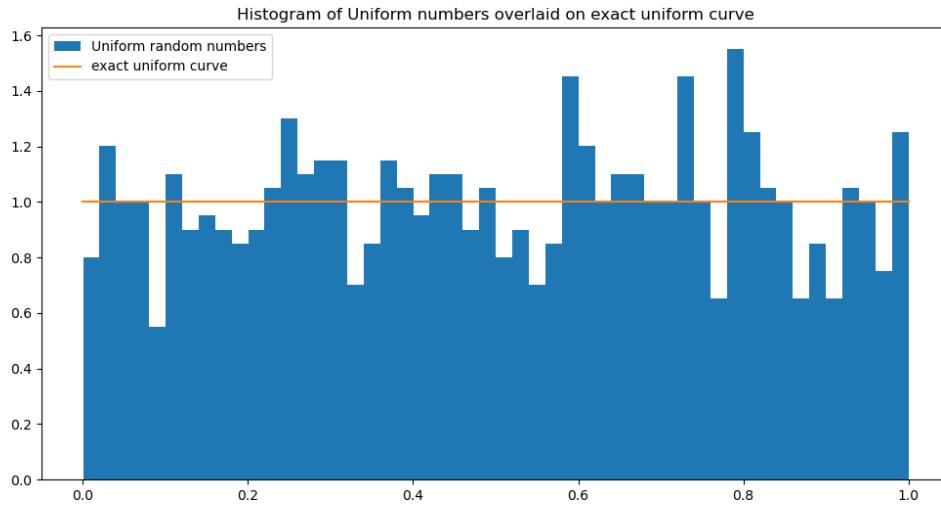
---

#### 1. UNIFORM AND NORMAL RANDOM VARIABLES.

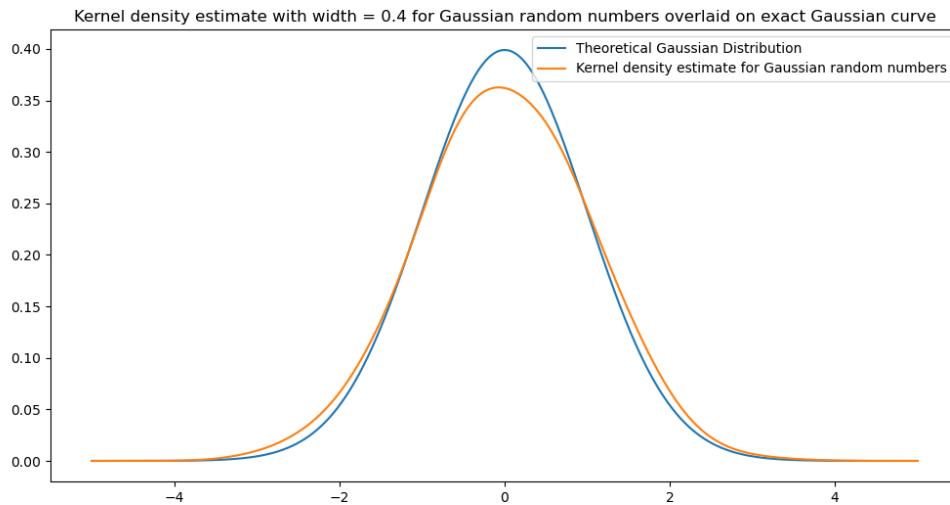
Histogram of Gaussian random numbers overlaid on exact Gaussian curve (scaled):



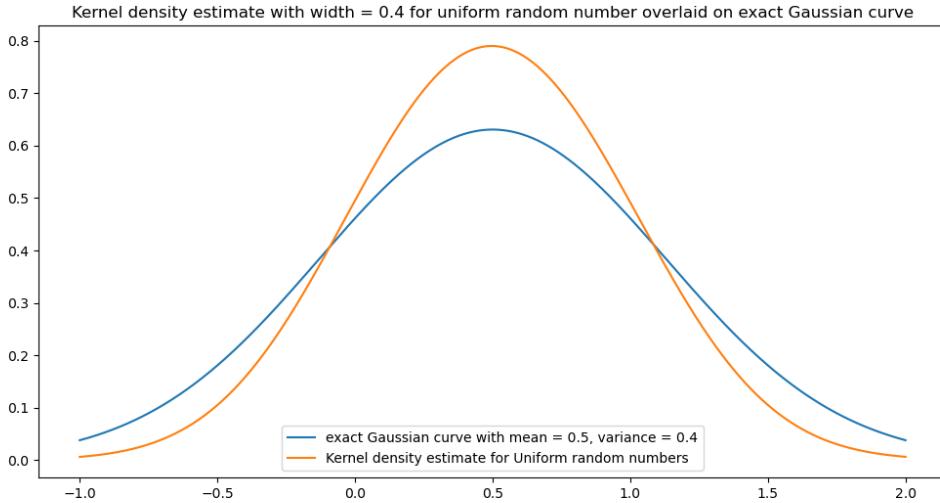
Histogram of Uniform random numbers overlaid on exact Uniform curve (scaled):



Kernel density estimate for Gaussian random numbers overlaid on exact Gaussian curve:



Kernel density estimate for Uniform random numbers overlaid on exact Gaussian curve:



**Comment on the advantages and disadvantages of the kernel density method compared with the histogram method for estimation of a probability density from random samples:**

According to the plots, kernel smoothing function works well with Gaussian random numbers. It is very close to the exact Gaussian curve. However, it does not perform well when it comes to uniform random numbers. We can see that the smoothing function of uniform random numbers is close to a Gaussian curve. This is due to large value of width applied in the kernel smoothing function. A large value of width underfits the random numbers and makes the smoothing function similar to the kernel function itself, which is a standard Gaussian distribution in this context.

If the width is set to smaller values, for example, 0.1. The smoothing function provides a good approximation to the expected probability density function, which is a constant from 0 to 1. But it overfits the data, the density curve is no longer a constant value as expected. It can be seen that fine-tuning on the width is much harder for uniform random numbers.

To sum up, kernel density method works well with Gaussian random numbers, and becomes harder to fine-tune the parameter to fit uniform random numbers.

**Theoretical mean and standard deviation calculation for uniform density as a function of  $N$ :**

Suppose a set of  $N$  independent random samples are taken from a uniform distribution:

$$x^{(i)} \sim p_U(x) = \frac{1}{N}, i = 1, \dots, N$$

The probability that a sample  $x^{(j)}$  lies within a particular bin of the histogram is:

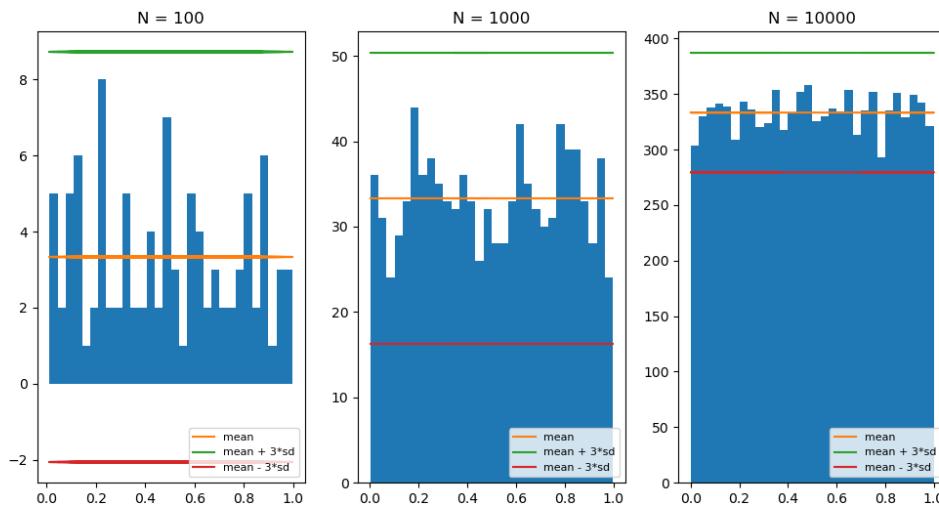
$$p_j = \int_{c_j-\delta/2}^{c_j+\delta/2} p(x)dx = \frac{\delta}{N}$$

in which  $\delta$  represents the size of a bin.

Thus, the mean of the count data in bin  $j$  is  $Np_j = \delta$ . The variance is  $Np_j(1 - p_j) = \delta(1 - \frac{\delta}{N})$

**Explain behaviour as  $N$  becomes large:** Assuming a constant bin size, it is clear that the mean is not affected by  $N$ , and the variance decreases as  $N$  increases.

**Plot of histograms for  $N = 100$ ,  $N = 1000$  and  $N = 10000$  with theoretical mean and  $\pm 3$  standard deviation lines:**



**Are your histogram results consistent with the multinomial distribution theory?** For the case that  $N = 1000$  and  $10000$ , the histogram results are consistent with the multinomial distribution theory. Considering the counts of each bin as a random variable, its distribution approaches to Gaussian distribution as  $N \rightarrow \infty$  according to Central Limit Theorem.

For a Gaussian distribution, 99% of random variable lies within the interval  $(\mu - 3\sigma, \mu + 3\sigma)$ . From the plots that  $N = 1000$  and  $N = 10000$ , we can see that it is true.

However, the plot of  $N = 100$  gives a negative value of  $\mu - 3\sigma$ . Since  $\sigma^2 = \delta(1 - \frac{\delta}{N})$ , a small  $N$  gives a large  $\sigma$ . This implies that histogram estimation is not suitable for a set of random numbers with a small size.

## 2. FUNCTIONS OF RANDOM VARIABLES

**For normally distributed  $\mathcal{N}(x|0, 1)$  random variables, take  $y = f(x) = ax + b$ . Calculate  $p(y)$  using the Jacobian formula:** The Jacobian formula provided by lab handout:

$$p(y) = \frac{p(x)}{|dy/dx|} \Big|_{x=f^{-1}(y)}$$

Explain how this is linked to the general normal density with non-zero mean and non-unity variance:

*Text/math answer here*

Verify this formula by transforming a large collection of random samples  $x^{(i)}$  to give  $y^{(i)} = f(x^{(i)})$ , histogramming the resulting  $y$  samples, and overlaying a plot of your formula calculated using the Jacobian:

*Include your graphic here*

Now take  $p(x) = \mathcal{N}(x|0, 1)$  and  $f(x) = x^2$ . Calculate  $p(y)$  using the Jacobian formula:

*Text/math answer here*

Verify your result by histogramming of transformed random samples:

*Include your graphic here*

### 3. Inverse CDF method

Calculate the CDF and the inverse CDF for the exponential distribution:

The pdf of an exponential distribution  $Y$  with mean 1 is:

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

The corresponding cdf is found by integration:

$$F_Y(y) = \int_0^y f_Y(t)dt = \int_0^y e^{-t}dt = 1 - e^{-y}$$

The inverse of this function is found by:  $x = F_Y(y), y = F_Y^{-1}(x)$ .

$$F_Y^{-1}(x) = -\ln(1-x)$$

Matlab/Python code for inverse CDF method for generating samples from the exponential distribution:

Listing 1: MATLAB

```
x_data = np.random.uniform(0,1,1000)
y_data = -np.log(1-x_data)

y = np.linspace(0,5,1000)
exp_theoretical = np.e**(-y)
```

Plot histograms/ kernel density estimates and overlay them on the desired exponential density:

*Include your graphic here*

#### 4. Simulation from a ‘non-standard’ density.

Matlab/Python code to generate  $N$  random numbers drawn from the distribution of  $X$ :

Plot some histogram density estimates with  $\alpha = 0.5, 1.5$  and several values of  $\beta$ .

Hence comment on the interpretation of the parameters  $\alpha$  and  $\beta$ .

## A Link to worked files

The worked python files are uploaded to a repository which can be found at: [https://github.com/OliverJiang2025/3F3\\_lab.git](https://github.com/OliverJiang2025/3F3_lab.git)