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## ENGINEERING TRIPOS PART II A

EIETL

MODULE EXPERIMENT 3F3

### RANDOM VARIABLES and RANDOM NUMBER GENERATION

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You should read this handout and understand the theory *before* you arrive for the laboratory session. Otherwise you will find it difficult to complete the experiment in the allotted time and you risk being penalised by the demonstrators. The lab can be completed using Matlab OR Python - you may choose which language to use

#### OBJECTIVES

- To introduce the idea of random variables and functions of random variables
- To study the Jacobian as used with random variables
- To experiment with methods for non-uniform random number generation

## 1 Introduction

Random number generation is a vital part of many engineering, computer science and physical science applications. Random numbers are used in simulation of physical systems, in performing inference in otherwise intractable problems and in the study of random phenomena such as mechanical vibrations, earthquakes, etc. While uniformly distributed pseudo-random numbers can readily be generated by several reliable means, how do we convert these uniform variates into samples from other desired distributions which may be required in particular applications?

In this practical we will study the generation of non-uniformly distributed random numbers in Matlab/Python, introducing some of the principal tricks involved in generation from desired probability distributions. We will assume that basic number generators for generating uniform or normally distributed random numbers are already available, as in Matlab. Random number generation will be used as a vehicle to demonstrate the theory of change of variables using Jacobians, as detailed below.

The Matlab commands `rand` and `randn` can be used to generate vectors of pseudo-random numbers from the uniform distribution:

$$p(x) = \mathcal{U}(x|0, 1) = \begin{cases} 1, & 0 < x < 1 \\ 0, & \text{otherwise} \end{cases}$$

or from the normal distribution (mean zero, variance 1):

$$p(x) = \mathcal{N}(x|0, 1) = \frac{1}{\sqrt{2\pi}} \exp(-x^2/2)$$

Sometimes for conciseness we will simply write  $\mathcal{U}(0, 1)$  or  $\mathcal{N}(0, 1)$  for these distributions. The equivalent commands in Python are `numpy.random.rand` and `numpy.random.randn`.

## 1.1 A few revision basics

The normal distribution:

$$\mathcal{N}(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-(x - \mu)^2/(2\sigma^2))$$

We will also use the exponential distribution:

$$p(x) = \mathcal{E}(x|\mu) = \frac{1}{\mu} \exp(-x/\mu), \quad x \geq 0.$$

where  $\mu$  is the mean.

The cumulative distribution function for a random variable:

$$F(x) = \Pr(X \leq x)$$

Probability density function:

$$p(x) = dF(x)/dx$$

Expectation of a random variable:

$$\mu = \mathbb{E}[X] = \int_{x=-\infty}^{\infty} xp(x)dx$$

Expectation of a *function*  $f(x)$  of a random variable:

$$\mathbb{E}[f(X)] = \int_{x=-\infty}^{\infty} f(x)p(x)dx$$

In the experiment we will sometimes refer to this formula as the expectation of  $f(x)$  wrt the probability density  $p(x)$ .

Variance of a random variable:

$$\sigma^2 = \mathbb{E}[(X - \mu)^2] = \mathbb{E}[X^2] - \mu^2$$

and  $\sigma$  is termed the *standard deviation* of  $X$ .

## 1.2 Histogram estimation

During the practical you will use histogram count data. Here we outline some of the theory of histogram counts which you can use in the practical.

Take a set of  $N$  independent random samples from a probability distribution:

$$x^{(i)} \sim p(x), \quad i = 1, \dots, N$$

We may estimate the shape of the density by histogramming the data (Matlab function `hist`, [Python function `matplotlib.pyplot.hist`](#)). The probability that a sample  $x^{(i)}$  lies within a particular bin of the histogram is:

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

where  $c_j$  is the  $j$ th bin centre,  $j = 1, \dots, J$ , and  $\delta$  the bin width. If we draw  $N$  random variables and count the number that lie within each bin, say  $n_j$ , the probability of the histogram data is given by:

$$\frac{N!}{n_1! n_2! \dots n_J!} p_1^{n_1} p_2^{n_2} \dots p_J^{n_J} \quad (1)$$

This is the *multinomial* distribution. The mean of the count data in bin  $j$  is  $Np_j$  and the variance is  $Np_j(1 - p_j)$ .

### 1.3 Matlab/Python and general Preparation

In order to get through this lab in the recommended time you will need to be familiar with basic Matlab functions and plotting capabilities. The following, largely uncommented, snippet of code gets you started on the first part of the practical. Make sure you understand the arguments supplied to the `hist` and `ksdensity` functions:

```
% Plot normal distribution:
```

```
figure(1)
```

```
x=randn(1000,1);
```

```
subplot(211),
```

```
hist(x,20)
```

```
subplot(212),
```

```
ksdensity(x,'width',0.1)
```

```
% Plot uniform distribution:
```

```
figure(2)
```

```
x=rand(1000,1);
```

```
subplot(211),
```

```
% Be aware that when specifying bin centres as below, Matlab will include everything
% from -infinity to the first bin centre in the first bin,
```

```
% and the top bin to +infinity in the last bin
```

```
hist(x,[-1.45:0.1:1.45])
```

```
subplot(212),
```

```
ksdensity(x,'width',0.1)
```



And for Python the `ksdensity` function is provided below:

```
import numpy as np
import matplotlib.pyplot as plt

def ksdensity(data, width=0.3):
    """Returns kernel smoothing function from data points in data"""
    def ksd(x_axis):
        def n_pdf(x, mu=0., sigma=1.): # normal pdf
            u = (x - mu) / abs(sigma)
            y = (1 / (np.sqrt(2 * np.pi) * abs(sigma)))
            y *= np.exp(-u * u / 2)
            return y
        prob = [n_pdf(x_i, data, width) for x_i in x_axis]
        pdf = [np.average(pr) for pr in prob] # each row is one x value
        return np.array(pdf)
    return ksd

# Plot normal distribution
fig, ax = plt.subplots(2)
x = np.random.randn(1000)
ax[0].hist(x, bins=30) # number of bins

ks_density = ksdensity(x, width=0.4)
# np.linspace(start, stop, number of steps)
x_values = np.linspace(-5., 5., 100)
ax[1].plot(x_values, ks_density(x_values))

# Plot uniform distribution
fig2, ax2 = plt.subplots(2)
x = np.random.rand(1000)
ax2[0].hist(x, bins=20)

ks_density = ksdensity(x, width=0.2)
x_values = np.linspace(-1., 2., 100)
ax2[1].plot(x_values, ks_density(x_values))

plt.show()
```

There are also some required theoretical calculations that can be drafted out before the experiment if you would like to speed your progress prior to the lab session itself - see below.

The whole practical can be carried out in your own time if preferred. However, you will need to attend at least the start of the lab session, and it is recommended to attend the whole session so that you can check your ideas and working with the demonstrators.

## 2 Experimental Work

1. **Uniform and normal random variables** Use Matlab/Python to generate a vector of 1000 Gaussian random numbers and 1000 uniform random variables. Plot histograms of the generated numbers and overlay these on plots of the exact normal and uniform probability density functions (scaled appropriately to match the histogram count data).

Experiment also with using the `ksdensity` function in Matlab/Python, to plot a smooth density function estimate from the samples using the formula:

$$\pi_{KS}(x) = \frac{1}{N} \sum_{i=1}^N \frac{1}{\sigma} \mathcal{K}\left(\frac{x - x^{(i)}}{\sigma}\right) \quad (2)$$

using for example the Gaussian kernel,  $\mathcal{K}(x) = \mathcal{N}(x|0, 1)$ . 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.

*Long report: Explain the form of the multinomial distribution; in particular why do we get the terms  $p_j^{n_j}$ , and why the factorial terms?*

For the uniform distribution, calculate the theoretical mean and standard deviation for the histogram count data, as a function of  $N$  (using the multinomial distribution theory from above). Explain what happens to the histogram estimate as  $N$  becomes large.

For  $N = 100$ ,  $N = 1000$  and  $N = 10000$ , plot the data histogram, the theoretical mean of the histogram data and also the  $\pm 3$  standard deviation lines. Are your histogram results consistent with the multinomial distribution theory? (in other words, are the histograms consistent with Matlab/Python having generated accurate uniformly distributed random variates?).

*Long report: repeat this for normally distributed data. Comment on how the histogram variance depends on the bin probabilities (consider  $p_i$  close to zero, one, and intermediate). For this part you will need to carefully calculate the bin probabilities  $p_j$  using the cdf function, `normcdf` in Matlab, `scipy.stats.norm.cdf` in Python.*

2. **Functions of random variables** In engineering systems, random variables very often pass through functions, for example we might take the magnitude or the squared value of a random signal when performing detection of ‘significant’ events. In other cases we might measure a sine or cosine function at a randomly chosen phase offset. Here we will study the distribution of these transformed random variables.

The theoretical answer involves the *Jacobian* of the transformation.

Consider a general function of the random variable  $x$ :

$$y = f(x)$$

If we know that  $x$  is distributed with density function  $p(x)$ , then we can calculate the output density  $p(y)$  as follows, assuming that  $f()$  is a one-to-one, invertible,

differentiable function:

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

If there is more than one possible value for  $f^{-1}(y)$ , say  $x_1(y), x_2(y), \dots, x_K(y)$ , then the solution is the sum over all possible solutions:

$$p(y) = \sum_{k=1}^K \frac{p(x)}{|dy/dx|} \Big|_{x=x_k(y)}$$

See the 3F3 lecture notes for the derivation and general case...

Example:

Take  $p(x) = \mathcal{U}(-0.5, +0.5)$ , i.e. uniform between  $-0.5$  and  $+0.5$ :

$$p(x) = \begin{cases} 1, & -0.5 < x < 0.5 \\ 0, & \text{Otherwise} \end{cases}$$

and  $f(x) = |x|$ . Now,

$$df(x)/dx = \begin{cases} 1, & x > 0 \\ -1, & x < 0 \end{cases}$$

and so the Jacobian is  $|dy/dx| = 1$  for all  $x \neq 0$  (undefined at  $x = 0$ ).

Now,  $y = |x|$  has two possible inverses, i.e.  $x_1(y) = y$  or  $x_2(y) = -y$ . Hence the new density function is:

$$p(y) = \sum_{k=1}^2 \frac{p(x)}{|dy/dx|} \Big|_{x=x_k(y)} = p(y)/1 + p(-y)/1 = \begin{cases} 2, & 0 < y < 0.5 \\ 0, & \text{Otherwise} \end{cases}$$

where the zero case takes account of  $p(x)$  being zero when  $|x| > 0.5$ . Thus in this simple case we get another uniform distribution,  $p(y) = \mathcal{U}(0, 0.5)$ , which of course has height equal to 2 to make it integrate to 1 as a probability density function.

Now, for normally distributed  $\mathcal{N}(x|0, 1)$  random variables, take  $y = f(x) = ax+b$ . Calculate  $p(y)$  using the Jacobian formula as above, and explain how this is linked to the general normal density with non-zero mean and non-unity variance. 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.

Now take  $p(x) = \mathcal{N}(x|0, 1)$  and  $f(x) = x^2$ . Calculate  $p(y)$  using the Jacobian formula and once again verify your result by histogramming of transformed random samples.

*Long report: Take  $p(x) = \mathcal{U}(x|0, 2\pi)$  and  $f(x) = \sin(x)$  - this corresponds to measuring e.g. a carrier signal in a comms. system at a random phase offset. Determine the theoretical probability density for  $f(x)$  and verify once again by comparison with transformed random samples. Now, instead of the sin function,*

consider a limited sin function, an idealised version of the ‘clipping’ or limiting that can occur when electronics saturate:

$$f(x) = \min(\sin(x), 0.7)$$

Determine experimentally from random samples what the output density is for  $y$  and comment on how this could be predicted from the Jacobian formula - pay particular attention to  $\sin(x) > 0.7$ .

3. **Inverse CDF method** Transformations of random variables leads to a very neat and general method for non-uniform random variable generation. Take  $p(x) = \mathcal{U}(x|0, 1)$ , and consider transforming  $x$  to some other distribution using  $y = f(x)$ , where now we assume the simple first case where  $f(x)$  is invertible and differentiable. Thus we have

$$p(y) = \begin{cases} \frac{1}{|dy/dx|} \Big|_{x=f^{-1}(y)}, & f^{-1}(y) \in (0, 1) \\ 0, & \text{otherwise} \end{cases}$$

Now, suppose that samples are required from a specified density function  $p(y)$  but we only have a uniform random number generator  $p(x) = \mathcal{U}(x|0, 1)$ . We can choose an appropriate  $f(x)$  which would achieve this. It [would](#) need to satisfy:

$$p(y) = \frac{1}{|dy/dx|} = |dx/dy| = |df^{-1}(y)/dy|$$

since  $(dy/dx)^{-1} = dx/dy$  by standard derivative calculus. If we assume a function can be chosen whose derivative is always greater than zero, then we would have a simpler equation:

$$p(y) = df^{-1}(y)/dy$$

But we know that the first derivative of the cumulative distribution function (CDF)  $F(y)$  is the density function, by definition. We know too that it is non-decreasing, so its derivative is always greater than (or equal to) zero, as required (assume the CDF is always strictly increasing for now, although the method presented here also works for the general case). Thus an appropriate solution is:

$$f^{-1}(y) = F(y),$$

or, equivalently:

$$f(x) = F^{-1}(x)$$

Thus, if we can evaluate the inverse CDF function  $F^{-1}(x)$ , we can generate exact random samples from  $p(y)$  by generating uniform samples  $x^{(i)} \sim \mathcal{U}(0, 1)$  and computing

$$y^{(i)} = F^{-1}(x^{(i)})$$

This is the inverse CDF method, one of the simplest and most general methods for generation of random variates with specified probability density.

Now consider the exponential distribution with mean one:

$$p(y) = \exp(-y), \quad y \geq 0$$

Calculate the CDF and the inverse CDF for this distribution.

Hence use the inverse CDF method to generate samples from the exponential distribution. Plot histograms/ kernel density estimates and overlay them on the desired exponential density to convince yourself of successful results.

*Long report: Use your random samples to estimate the mean and variance of the exponential distribution, and verify that they are close to the expected theoretical values for this exponential distribution. The mean can be estimated by Monte Carlo:*

$$\mu = \mathbb{E}[Y] = \int_{y=0}^{\infty} yp(y)dy \approx \frac{1}{N} \sum_{i=1}^N y^{(i)} = \hat{\mu}$$

*Intuitively, the Monte Carlo approach estimates expectation of a function  $f(x)$  by simply taking the arithmetic mean of the sampled function values  $f(x^{(i)})$ .*

*Long Report: Show that the Monte Carlo mean estimate  $\hat{\mu}$  is unbiased, i.e. that  $\mathbb{E}[\hat{\mu}] = \mu$ , where the first expectation is taken wrt the distribution of the random samples  $y^{(i)}$ , i.e.  $p(y)$ .*

*The variance can be estimated in a similar way by Monte Carlo:*

$$\sigma^2 = \mathbb{E}[Y^2] - \mu^2 = \int_{y=0}^{\infty} y^2 p(y)dy - \mu^2 \approx \frac{1}{N} \sum_{i=1}^N (y^{(i)})^2 - (\hat{\mu})^2 = \hat{\sigma}^2$$

*Optional Challenge (Long Report): show from expectation formulae that the Monte Carlo mean estimator has variance equal to  $\sigma^2/N$ , i.e. that*

$$\mathbb{E}[\hat{\mu}^2 - \mu^2] \propto 1/N$$

*Once again, the expectation is taken wrt the distribution of the  $y^{(i)}$ s.*

*Long Report: Illustrate this property by plotting the squared error  $(\hat{\mu} - \mu)^2$  as the number of Monte Carlo samples increases. This should strictly be done by averaging the error over lots of Monte Carlo estimates of  $\mu$  from different samples  $y^{(i)}$ , but you should be able to see the trend clearly from one set of samples. Here you are showing that the Monte Carlo estimator is also consistent in that it delivers the true value of  $\mu$  as the number of samples  $N$  goes to infinity. Note that this is considered quite a slow convergence rate as the values of the estimate only converge as  $1/\sqrt{N}$  and hence Monte Carlo should only be used when other approximations fail.*

4. **Simulation from non-standard densities.** Sometimes random variables cannot be simulated using inverse cdf or other convenient means. However, in such cases there may still be numerical ‘recipes’ for generating such variables. One method of generating some less straightforward random variables is using a Scale mixture of Normals representation. This works when a probability density function can be rewritten in the form of a Normal distribution for  $X$  with a random



variance  $U$ , drawn from some probability density function  $p(u)$ . Then, the distribution of  $X$  can be obtained by marginalisation:

$$\begin{aligned}p(x|u) &= \mathcal{N}(x|0, u) \\p(x, u) &= p(x|u)p(u) \\p(x) &= \int_0^\infty p(x|u)p(u)du \\&= \int_0^\infty \mathcal{N}(x|0, u)p(u)du\end{aligned}\tag{3}$$

Why is the range of integration from 0 to  $\infty$ ?

Many different probability distributions can be written as scaled mixtures of Normals. They each have distinctive ‘mixing distributions’ - the probability density function which determines the variance of the Normal component,  $p(u)$ . You will now generate samples from one such distribution.

1. Pick a value for parameter  $\alpha > 0$ .
2. Generate a sample of an exponential random variable,  $p(u) = (\alpha^2/2) \exp(-\alpha^2 u/2)$ .
3. Generate a single sample from a Normal distribution using the sampled variance  $p(x|u) = \mathcal{N}(x|0, u)$ .
4.  $x$  is the variable of interest. Repeat steps 2-4 for each sample.

What effect does  $\alpha$  have on the resulting distribution of  $X$ ?

Compare the shape of the distribution to that of a Normal distribution. Plot the logarithm of the kernel density estimate (be careful around the origin) for different values of  $\alpha$  and use this to suggest a formula for  $p(x)$ .

Long report: You will now investigate another distribution formed by a scaled mixture of Gaussians. Instead of the exponential distribution, you will use the gamma distribution:

$$\mathcal{G}(x|a, b) = \frac{1}{b^a \Gamma(a)} x^{a-1} e^{-\frac{x}{b}}$$

where  $a$  and  $b$  are positive valued parameters. Here,  $\Gamma(\cdot)$  represents the gamma function, which is the normalising constant of the density (it ensures that the pdf integrates to 1). The gamma function is available as a Matlab and Python function.

First, familiarise yourself with the distribution by setting some different parameters,  $a$ , and,  $b$ , and plotting some histograms of samples. Sampling can be done in Python using `numpy.random.gamma(shape, scale, size)` and in Matlab using `gamrnd(shape, scale, [1, size])`, where `shape` =  $a$ , `scale` =  $b$ , and `size` is the number of samples.

The recipe for generating  $X$  is now:

- (a) Pick a value for parameter  $\theta > 0$ .
- (b) Generate a sample from the Gamma distribution,  $p(v) = \mathcal{G}(v|\theta, 1/\theta)$ .
- (c) Calculate the variance as  $u = 1/v$ .
- (d) Sample from a Normal distribution  $p(x|u) = \mathcal{N}(x|0, u)$ .
- (e)  $x$  is the random variable of interest.

How does  $\theta$  affect the final distribution? What happens as  $\theta$  gets large? How does the resulting distribution differ from the previous one with an exponential mixing distribution?

Investigate the tail behaviour for large values of  $|x|$ , and suggest an approximate formula for the tails in the form  $p(x) \propto |x|^{-\beta}$ , where  $\beta$  will be related to  $\theta$ , using suitably devised logarithmic kernel density plots.

Determine the probability density function for  $U = 1/V$  by the Jacobian method.

Now derive the formula for  $p(x)$  using equation 3 and your expression for  $p(u)$ . The result should be expressed in terms of the gamma function,  $\Gamma(\cdot)$ ,  $x$  and  $\theta$ . Is this formula consistent with your analysis of the tail behaviour above?

HINT: There are several ways to perform this integral. You may find it convenient to integrate by substitution with  $v = 1/u$ , and then use the fact that the gamma pdf must integrate to 1, for all positive values of  $a$  and  $b$ :

$$\int_0^\infty \frac{1}{b^a \Gamma(a)} x^{a-1} e^{-\frac{x}{b}} dx = 1$$

and hence that:

$$\int_0^\infty x^{a-1} e^{-\frac{x}{b}} dx = b^a \Gamma(a)$$

### 3 Write-up.

All reports are to be handed in electronically through the 3F3 Moodle website, within the general deadlines specified for IIA coursework.

#### The Laboratory Report (Short Report)

In the short report, provide answers to all of the questions and tasks in the instructions. You should include brief and clear derivations of any required theoretical results, Matlab/Python graphs of results and you should cut and paste the code you wrote for each part into the relevant section of the report.

You may write the report in Latex (recommended) or Word.

For the short report you are *not* required to include introduction/ methods/ apparatus/ conclusion sections. Rather, you may follow the template provided on the Moodle page for 3F3, including your results and calculations at each step. You do not need to provide responses to the items in italics beginning ‘*Long Report:*’

#### The Long Report

The Long report requires a couple of hours of extra coding work plus a more detailed write-up. For the long report, provide a full write-up of the practical, including the extra ‘*Long Report:*’ items. You should have an Introduction and Conclusion, with clearly reasoned answers to all questions, from both the short and long report topics.