NUEN 647
Uncertainty Quantification for Nuclear Engineering
Assignment 1

Due on Tuesday, October 4, 2016

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Contents

Complete the exercises in the Chapter 2 notes. Be sure to include discussion of results where appropriate. You may use any tools that are approrpriate to solving the problem.

Problem 1

Show that the transformation in equation 1 results in a standard normal random variable by computing the mean and variance of z.

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

An important special case of the expectation value is the mean which is the expected value of x. It is often denoted as μ,

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

where x is a realization of a random sample and $f(x)$ is the probability density function (PDF) for the random variable. For a normal distribution,

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

For the sake of the transformation, the value of z substitutes for x, the realization of a random sample (not the PDF because we are transforming that distribution). Therefore, the mean for z is:

$$\mu_z = \int_{-\infty}^{\infty} \frac{x-\mu}{\sigma} \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx$$

If $u = (x-\mu)^2$ and $\frac{du}{2} = (x-\mu)dx$ (note that the limits change from $(-\infty, \infty)$ to (∞, ∞) - but that seems fishy to me so I will change it back after integration).

$$\mu_z = \int_{\infty}^{\infty} \frac{1}{2\sigma^2\sqrt{2\pi}} e^{\frac{-u}{2\sigma^2}} du = \left| \frac{-1}{\sqrt{2\pi}} e^{\frac{-u}{2\sigma^2}} \right|_{\infty}^{\infty}$$

$$\mu_z = \left| \frac{-1}{\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \right|_{-\infty}^{\infty} = \frac{-1}{\sqrt{2\pi}} (e^{-\infty} - e^{-\infty}) = \boxed{0}$$

The variance is defined as:

$$Var(X) = E[(X-\mu_X)^2]$$

Substituting Eq. 1 for X, (but not for the pdf)

$$Var(Z) = E[(\frac{x-\mu_X}{\sigma_X} - \mu_Z)^2] = E\left[\left(\frac{x-\mu_X}{\sigma_X}\right)^2\right] = \frac{1}{\sigma_X^2}(E[x^2] - 2\mu_X E[x] + \mu^2 E[1])$$

Noting that above it was proven that $E[x] = \mu_X$ and given that the definition of $E[1] = 1$ and assuming that $E[x^2] = \sigma_X^2 + \mu_X^2$ (will solve on next page)

$$\frac{1}{\sigma_X^2}(\sigma_X^2 + \mu_X^2 - 2\mu_X^2 + \mu_X^2) = \boxed{1}$$

$$E[x^2] = \int_{-\infty}^{\infty} \frac{x^2}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

If $t = \frac{(x-\mu)}{\sqrt{2}\sigma}$ and $\sqrt{2}\sigma dt = dx$ and $x = t\sqrt{2}\sigma + \mu$ then (limits of integration don't change)

$$E[x^2] = \int_{-\infty}^{\infty} \frac{\left(t\sqrt{2}\sigma + \mu\right)^2}{\sqrt{\pi}} e^{-t^2} dt = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} \left(2\sigma^2 \left(t^2 e^{-t^2}\right) + 2\sqrt{2}\sigma\mu \left(te^{-t^2}\right) + \mu^2 \left(e^{-t^2}\right)\right)$$

According to wolfram alpha

$$\int_{-\infty}^{\infty} t^2 e^{-t^2} = \frac{\sqrt{\pi}}{2}$$

$$\int_{-\infty}^{\infty} te^{-t^2} = 0$$

$$\int_{-\infty}^{\infty} e^{-t^2} = \sqrt{\pi}$$

Which simplifies the above to $\sigma^2 + \mu^2$.

Problem 2

Consider the random variables $X \sim U(-1, 1)$ and $Y \sim X^2$. Are these independent random variables? What is their covariance?

Marginal and Joint PDFs

The PDF for X is:

$$f_X(x) = \frac{1}{(1-(-1))} = 0.5 \quad x \in [-1, 1]$$

The PDF for Y is: ^{link}

$$f_Y(y) = \frac{1}{2\sqrt{y}} \quad y \in [0, 1]$$

Without using the handy reference, this may be derived from the joint PDF, $f(x, y)$, defined as (between McClarrens Eq. 2.30 and 2.31):

$$f(x, y) = f(y|x) f_X(x)$$

From the definition of Y, $f(y|x)$ is 0 except when $y = x^2$. I think this would be.

$$f(y|x) = \delta(y - x^2)$$

Which means,

$$f(x, y) = 0.5\delta(y - x^2)$$

To calculate the PDF for Y (f(y)), we need to integrate over all other variables (in this case, X).

$$f(y) = \int_{-1}^{1} f(x, y) dx = \int_{-1}^{1} 0.5\delta(y - x^2) dx$$

Wolfram alpha tells me the answer is,

$$f_Y(y) = \frac{1}{2\sqrt{y}} \quad y \in [0, 1]$$

The same as above.

Independance

If two random variables, X and Y, are independent, they satisfy the following condition: ^{link}

- $P(Y|X) = P(Y)$, for all values of X and Y.

Because $P(Y|X) = \delta(y - xY2) \neq P(Y) = \frac{1}{2\sqrt{y}}$ (at least not for ALL values of x and y), these two variables are $\boxed{dependent}$.

Problem 2 continued on next page...

Covariance

The covariance for two random variables is defined as:

$$\sigma_{XY} = E[(x - \mu_X)(y - \mu_Y)]$$

This simplifies down to:

$$\sigma_{XY} = E(XY) - \mu_X \mu_Y = \int_{-1}^{1} dx \int_{0}^{1} dy \;\; xyf(x,y) - \mu_X \mu_Y$$

Because $\mu_X = 0$ this reduces to

$$\begin{aligned} \sigma_{XY} = E(XY) &= \int_{-1}^{1} dx \int_{0}^{1} dy \;\; xyf(x,y) \\ &= \int_{-1}^{1} dx \int_{0}^{1} dy \;\; xy0.5\delta(y - x^2) \\ &= \int_{-1}^{1} dx \;\; 0.5x^3 dx \\ &= \boxed{0} \end{aligned}$$

Wolfram alpha gave the step between the second and third line. These variables are dependant, but have a zero covariance.

Problem 3

Show that a general covariance matrix must be positive definite, i.e. $\vec{x}^T \Sigma \vec{x} > 0$ for any vector $\vec{x}$ that is not all zeros.

Given that $\vec{Y}$ is a vector of random variables and $\vec{\mu}_Y$ is a vector of the mean values for the random variables found in $\vec{Y}$.

$$\begin{aligned}\vec{x}^T \Sigma \vec{x} &= \vec{x}^T E[(\vec{Y} - \vec{\mu}_Y)(\vec{Y} - \vec{\mu}_Y)^T]\vec{x} \\ &= E[\vec{x}^T (\vec{Y} - \vec{\mu}_Y)(\vec{Y} - \vec{\mu}_Y)^T \vec{x}]\end{aligned}$$

The last step above puts a constant inside the expectation value integral. Notice

$$\vec{x}^T (\vec{Y} - \vec{\mu}_Y) = (\vec{Y} - \vec{\mu}_Y)^T \vec{x}$$

and that both are scaler functions of the random variables. Therefore,

$$\begin{aligned}\vec{x}^T \Sigma \vec{x} &= E[(\vec{x}^T (\vec{Y} - \vec{\mu}_Y))^2] \\ &= E[g(\vec{Y})^2] = \sigma_f^2\end{aligned}$$

The expectation value for a multivariate distribution is defined as

$$E[g(\vec{Y})] = \int_{-\infty}^{\infty} dy_1 \int_{-\infty}^{\infty} dy_2 \ ... \int_{-\infty}^{\infty} dy_p \ g(\vec{y}) f(\vec{y})$$

Where $f(\vec{y})$ is the multivariate PDF for the random variables of $\vec{Y}$. If a number of samples is given, rather than functions that can be integrated, the expectation value for a multivariate distribution is defined as:

$$E[g(\vec{Y})] = SC$$

To prove that the covariance matrix is positive definite the above integral must be proved to be positive with $g(x) = (\vec{x}^T (\vec{Y} - \vec{\mu}_Y))^2$. Explicitly,

$$\begin{aligned}E[g(Y)] &= \int_{-\infty}^{\infty} dy_1 \int_{-\infty}^{\infty} dy_2 \ ... \int_{-\infty}^{\infty} dy_p \ (\vec{x}^T (\vec{Y} - \vec{\mu}_Y))^2 f(y) \\ &= \int_{-\infty}^{\infty} dy_1 \int_{-\infty}^{\infty} dy_2 \ ... \int_{-\infty}^{\infty} dy_p \ ((y_1 - \mu_1)x_1 + (y_2 - \mu_2)x_2 + \ ... \ + (y_p - \mu_p)x_p)^2 f(y)\end{aligned}$$

Problem 4

Use rejection sampling to sample from a Gamma random variable $X \sim \mathscr{G}(\alpha, \beta)$ where

$$f(x) = \frac{\theta^{\alpha-1} e^{-\theta\beta}}{\Gamma(\alpha)\beta^{-\alpha}} \quad \alpha, \beta > 0$$

Let $\alpha = 1$ and $\beta = 0.5$. From rejection sampling with a $N = 10^4$, compute a rejection rate for the sampling procedure. Now draw a triangle around the function and do rejection sampling. Compare the rejection rate from the triangle versus the rectangle. You may consider that the PDF is zero if $f(x) < 10^{-6}$.

Python script for rejection sampling.

Listing 1: Python Script for problem

```
#!/usr/bin/env python3

#################################################################
#################### Import packages #########################
#################################################################

import time
start_time = time.time()
import scipy.special as sps
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
import random as rn
import Functions as fun
import copy

#################################################################
###################### Calculations #########################
#################################################################

#Values go to 10^-6 around 26.245
N=100;alpha=1;beta=0.5;a=0;b=26.245;h=0.5;Nsamples=10**4

theta=np.linspace(a,b,N)
f_x=fun.GammaPDF(alpha,beta,theta)

(fig,ax)=fun.Plot(theta,f_x)

OutsideSquare=0;OutsideTri=0
for i in range(0,Nsamples):
    X=rn.uniform(a,b);Xt=copy.copy(X)
    Y=rn.uniform(0,h);Yt=copy.copy(Y)

    if Y>(-h/b)*X+h: #Triangular
        Xt=b-Xt
        Yt=h-Yt

    H=fun.GammaPDF(alpha,beta,X) #Square
    Ht=fun.GammaPDF(alpha,beta,Xt) #Triangle

```

```
    if(Y<H): #Square
        ax=fun.PlotaxIn(X,Y,i,ax,1)
    else:
        OutsideSquare=OutsideSquare+1
        ax=fun.PlotaxOut(X,Y,i,ax,1)

    if(Yt<Ht): #Triangular
        ax=fun.PlotaxIn(Xt,Yt,i,ax,2)
    else:
        OutsideTri=OutsideTri+1
        ax=fun.PlotaxOut(Xt,Yt,i,ax,2)

ax=fun.Plotlegend(ax,theta,f_x)

RejectionSq=OutsideSquare/Nsamples;RejectionTri=OutsideTri/Nsamples

print("Square = "+str(RejectionSq)+" Triangle = "+str(RejectionTri))
plt.savefig('P4F1.pdf')

##################### Time To execute ################
print("--- %s seconds ---" % (time.time() - start_time))
```

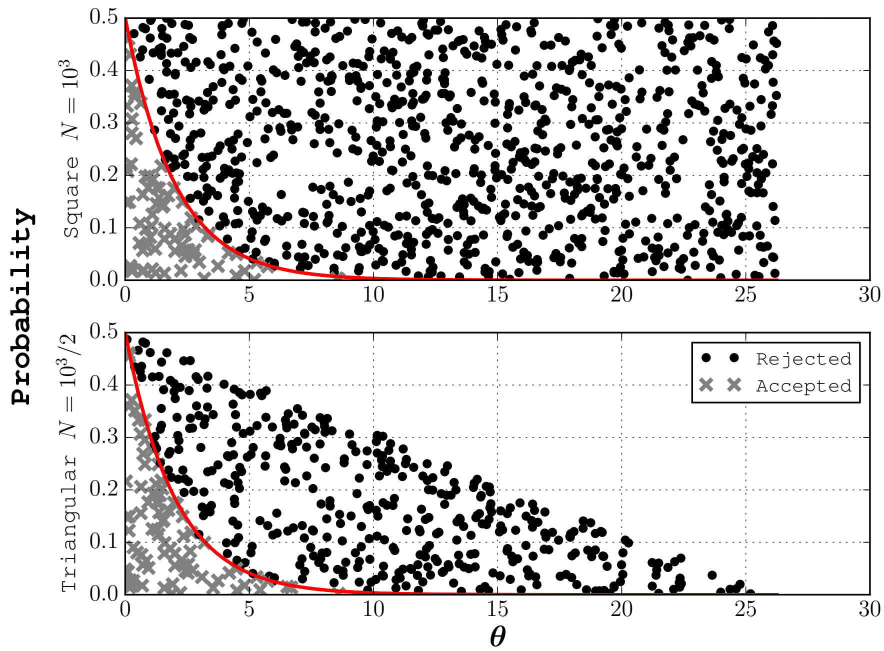

Figure 1: Square (top) and triangular (bottom) rejection sampling for the Gamma random variable.

The rejection rate for the square is $\boxed{92.65\%}$.
The rejection rate for the triangle is $\boxed{85.04\%}$.

The acceptance rate about doubled from the square to the triangle $((1-0.9265)*2 = 0.147 \approx 0.1496 = (1-0.8504))$. This is what is expected because we cut the sampling area in half. This could also be used to verify the PDF is properly normalized. $0.1496 * 0.5 * 26.245 * 1/2 = 0.98$.

Problem 5

Consider a random variable, $X > 0$, that has it's logarithm distributed by a normal distribution with mean $\mu = 0$ and variance $\sigma^2 = 1$. Such a distribution is called a log-normal distribution. Compute this distribution's a) mean, b) variance, c) median, d) mode, e) skew, and d) kurtosis.

The PDF for the log-normal distribution, found on wikipedia, is:

$$f(X) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(ln(x)-\mu)^2}{2\sigma^2}}$$

For a standard log-normal distribution this is

$$f(X) = \frac{1}{x\sqrt{2\pi}} e^{-\frac{ln(x)^2}{2}}$$

Which simplifies to:

$$\begin{aligned} f(X) &= \frac{1}{x\sqrt{2\pi}} \left(e^{-ln(x)}\right)^{\frac{ln(x)}{2}} \\ &= \frac{1}{x\sqrt{2\pi}} \left(\frac{1}{x}\right)^{\frac{ln(x)}{2}} \end{aligned}$$

a) mean

The mean, μ, is defined as:

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

Solving for the log-normal distribution mean:

$$\begin{aligned} \mu = E[x] &= \int_0^{\infty} \frac{1}{\sqrt{2\pi}} \left(\frac{1}{x}\right)^{\frac{ln(x)}{2}} dx \\ &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \left(\frac{1}{x}\right)^{\frac{ln(x)}{2}} dx \end{aligned}$$

Wolfram alpha says

$$\int_0^{\infty} \left(\frac{1}{x}\right)^{\frac{ln(x)}{2}} dx = \sqrt{2e\pi}$$

Therefore the answer is $\boxed{\sqrt{e}}$

This is an example citation [1].

References

[1] E. T. Tatro, S. Hefler, S. Shumaker-Armstrong, B. Soontornniyomkij, M. Yang, A. Yermanos, N. Wren, D. J. Moore, and C. L. Achim. Modulation of bk channel by microrna-9 in neurons after exposure to hiv and methamphetamine. *J Neuroimmune Pharmacol*, 2013. Tatro, Erick T Hefler, Shannon Shumaker-Armstrong, Stephanie Soontornniyomkij, Benchawanna Yang, Michael Yermanos, Alex Wren, Nina Moore, David J Achim, Cristian L R03 DA031591/DA/NIDA NIH HHS/United States U19 AI096113/AI/NIAID NIH HHS/United States Journal article Journal of neuroimmune pharmacology : the official journal of the Society on NeuroImmune Pharmacology J Neuroimmune Pharmacol. 2013 Mar 19.