

**NUEN 647**  
**Uncertainty Quantification for Nuclear Engineering**  
**Homework 3**

Due on Saturday, December 10, 2016

*Dr. McClarren*

**Paul Mendoza**

## Contents

<b>Problem 1</b>	<b>3</b>
<b>Problem 2</b>	<b>14</b>
<b>Problem 3</b>	<b>16</b>
<b>Problem 4</b>	<b>20</b>
<b>Problem 5</b>	<b>26</b>

## Problem 1

Fit the data in Table 1 to a linear model using

- (a) Least squares
- (b) Ridge Regression
- (c) Lasso Regression

Table 1: Data to fit linear model  $y = a + bx_1 + cx_2$

	$x_1$	$x_2$	$y$
1	0.99	0.98	6.42
2	-0.75	-0.76	0.20
3	-0.50	-0.48	0.80
4	-1.08	-1.08	-0.57
5	0.09	0.09	4.75
6	-1.28	-1.27	-1.42
7	-0.79	-0.79	1.07
8	-1.17	-1.17	0.20
9	-0.57	-0.57	1.08
10	-1.62	-1.62	-0.15
11	0.34	0.35	2.90
12	0.51	0.51	3.37
13	-0.91	-0.92	0.05
14	1.85	1.86	5.50
15	-1.12	-1.12	0.17
16	-0.70	-0.70	1.72
17	1.19	1.18	3.97
18	1.24	1.23	6.38
19	-0.52	-0.52	3.29
20	-1.41	-1.41	-1.49

Be sure to do cross-validation for each fit, and for each method present your best estimate of the model.

Did this problem in R, and appended the PDF on the following pages.

# Problem1

*Paul Mendoza*

*December 9, 2016*

```
require(magrittr)
require(dplyr)
require(ggplot2)
require(glmnet)
```

Fit the data in Table 1 to a linear model using:

Table1

```
##      x1    x2    y
## 1  0.99  0.98  6.42
## 2 -0.75 -0.76  0.20
## 3 -0.50 -0.48  0.80
## 4 -1.08 -1.08 -0.57
## 5  0.09  0.09  4.75
## 6 -1.28 -1.27 -1.42
## 7 -0.79 -0.79  1.07
## 8 -1.17 -1.17  0.20
## 9 -0.57 -0.57  1.08
## 10 -1.62 -1.62 -0.15
## 11  0.34  0.35  2.90
## 12  0.51  0.51  3.37
## 13 -0.91 -0.92  0.05
## 14  1.85  1.86  5.50
## 15 -1.12 -1.12  0.17
## 16 -0.70 -0.70  1.72
## 17  1.19  1.18  3.97
## 18  1.24  1.23  6.38
## 19 -0.52 -0.52  3.29
## 20 -1.41 -1.41 -1.49
```

## 1. Least Squares

```
LeastFit<-lm(formula = y~x1+x2,data=Table1)
LeastFit
```

```
##
## Call:
## lm(formula = y ~ x1 + x2, data = Table1)
##
## Coefficients:
## (Intercept)          x1          x2
##      2.606      38.133     -35.900
```

```

plotDF<-Table1
plotDF[, 'Type']<-'Train'
plotDF$Predict<-predict(LeastFit,plotDF[,1:2])
plotDF$Error<-plotDF$y-plotDF$Predict
ggplot(plotDF,aes(x=y,y=Predict,size=abs(Error)))+geom_point()+
  scale_size("Absolute Error")+geom_smooth(method="lm",se=F,size=1)

```



```

sqrt(var(data.frame(plotDF %>% filter(Type=="Train") %>% select(Error))))/20

```

```

##          Error
## Error 0.04902635

```

```

ggplot(plotDF,aes(x=Error)) + geom_histogram()

```



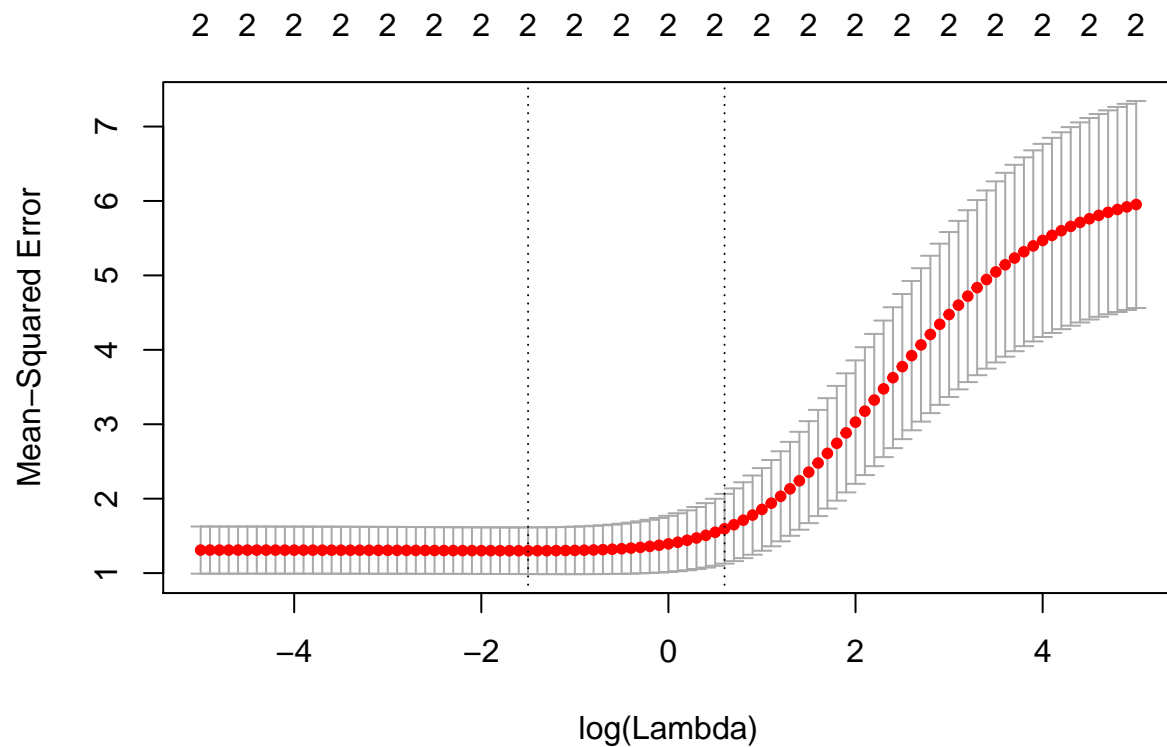
```
sensitivities <- coef(LeastFit)
sensDF <- data.frame(Method = 0, Var = 0, Value=0)
sensDF[1:length(sensitivities), 'Method'] <- "Least-Squares"
sensDF[1:length(sensitivities), 'Var'] <- names(sensitivities)
sensDF[1:length(sensitivities), 'Value'] <- (sensitivities)
rowStart <- length(sensitivities)+1
```

## 2. Ridge Regression

Ridge regression sets  $\alpha=0$ , which adds damping to the coefficients

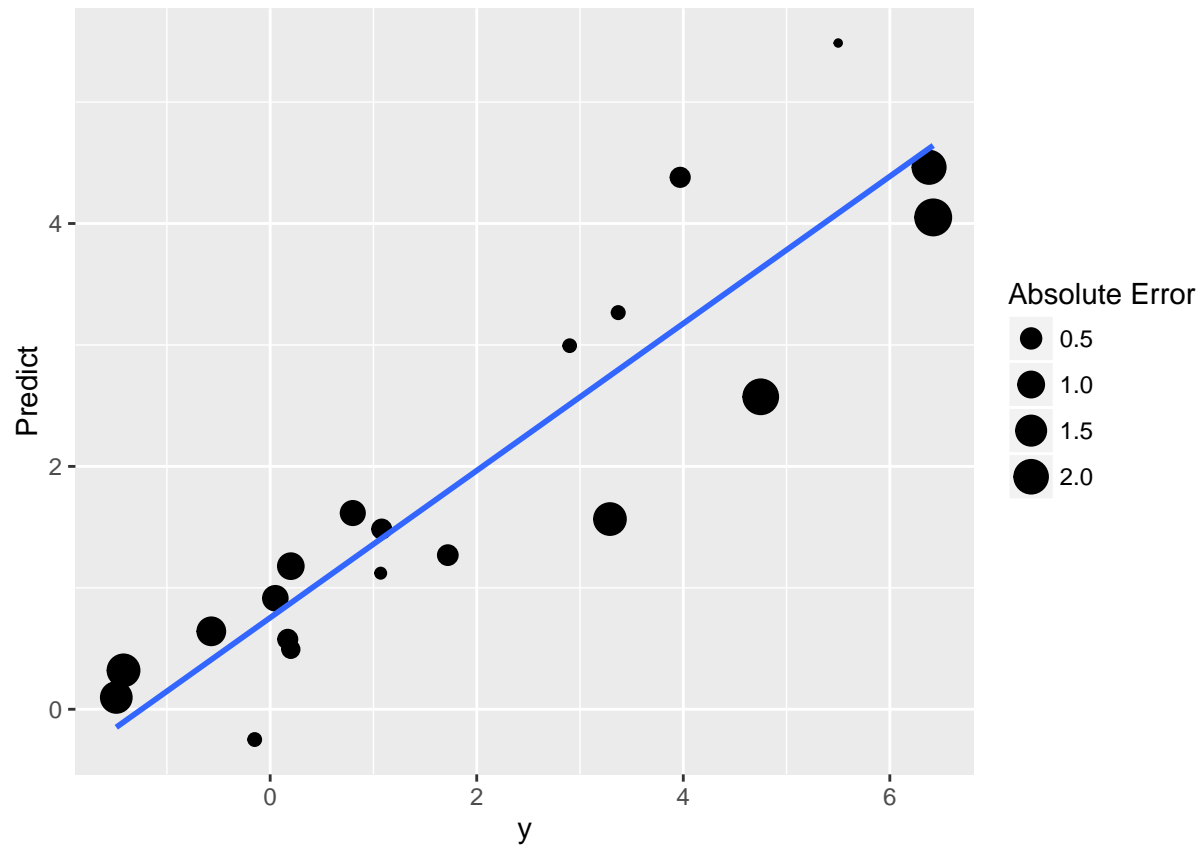
```
crossValid <- cv.glmnet(as.matrix(Table1[,1:2]),
                        as.matrix(Table1$y), alpha = 0,
                        lambda=exp(seq(-5,5,by=0.1)))

plot(crossValid)
```



```
lambda <- crossValid$lambda.min
sensitivities <- coef(crossValid)
plotDF <- Table1
plotDF[, 'Type'] <- 'Train'
plotDF[, "Predict" ]<- data.frame(Predict=predict(crossValid,as.matrix(plotDF[,1:2]),
                                                lambda=lambda))

plotDF$Error <- plotDF$y-plotDF$Predict
ggplot(plotDF,aes(x=y,y=Predict,size=abs(Error))) + geom_point() +
scale_size("Absolute Error") + geom_smooth(method="lm",se=F,size=1)
```



```
sqr t(var(data.frame(plotDF %>% filter(Type=="Train") %>% select(Error))))/20
```

```
##          Error
## Error 0.05982956
```

```
ggplot(plotDF,aes(x=Error)) + geom_histogram()
```



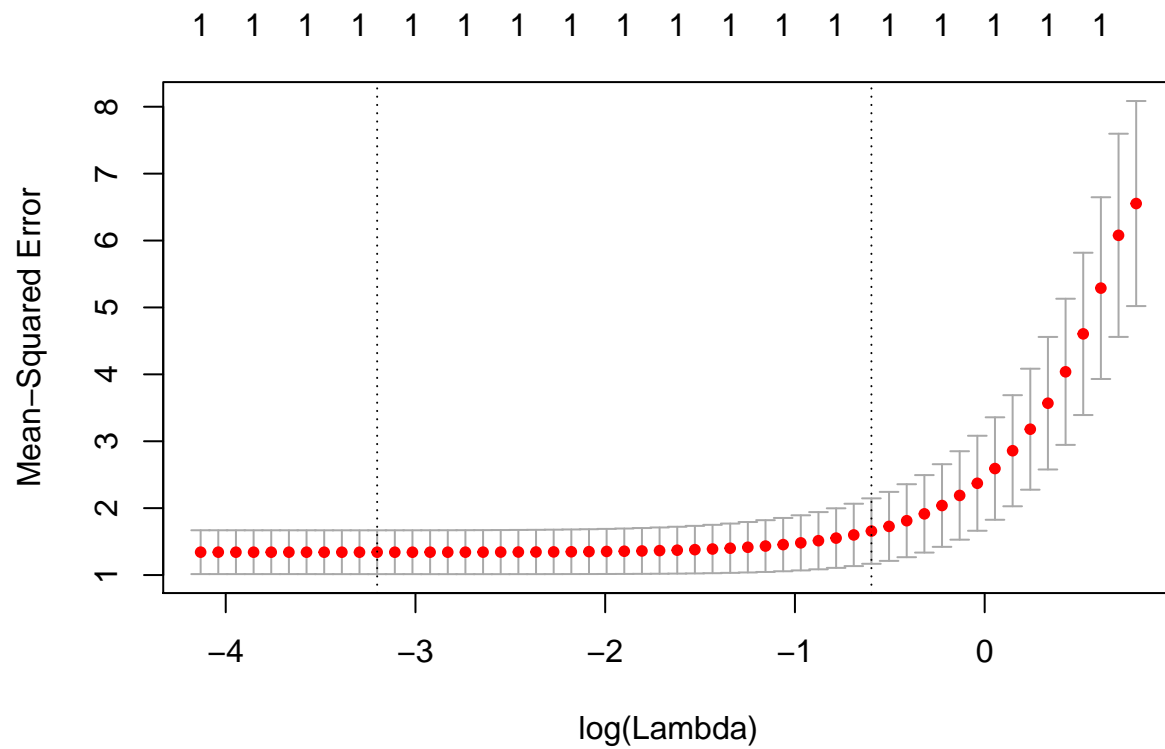


```
sensDF[rowStart:(rowStart + length(sensitivities)-1), 'Method'] <- "Ridge"
sensDF[rowStart:(rowStart+length(sensitivities)-1), 'Var']<-t(t(rownames(sensitivities)))
sensDF[rowStart:(rowStart +length(sensitivities)-1), 'Value']<-as.numeric(sensitivities)
rowStart <- rowStart + length(sensitivities)
```

### 3. Lasso Regression

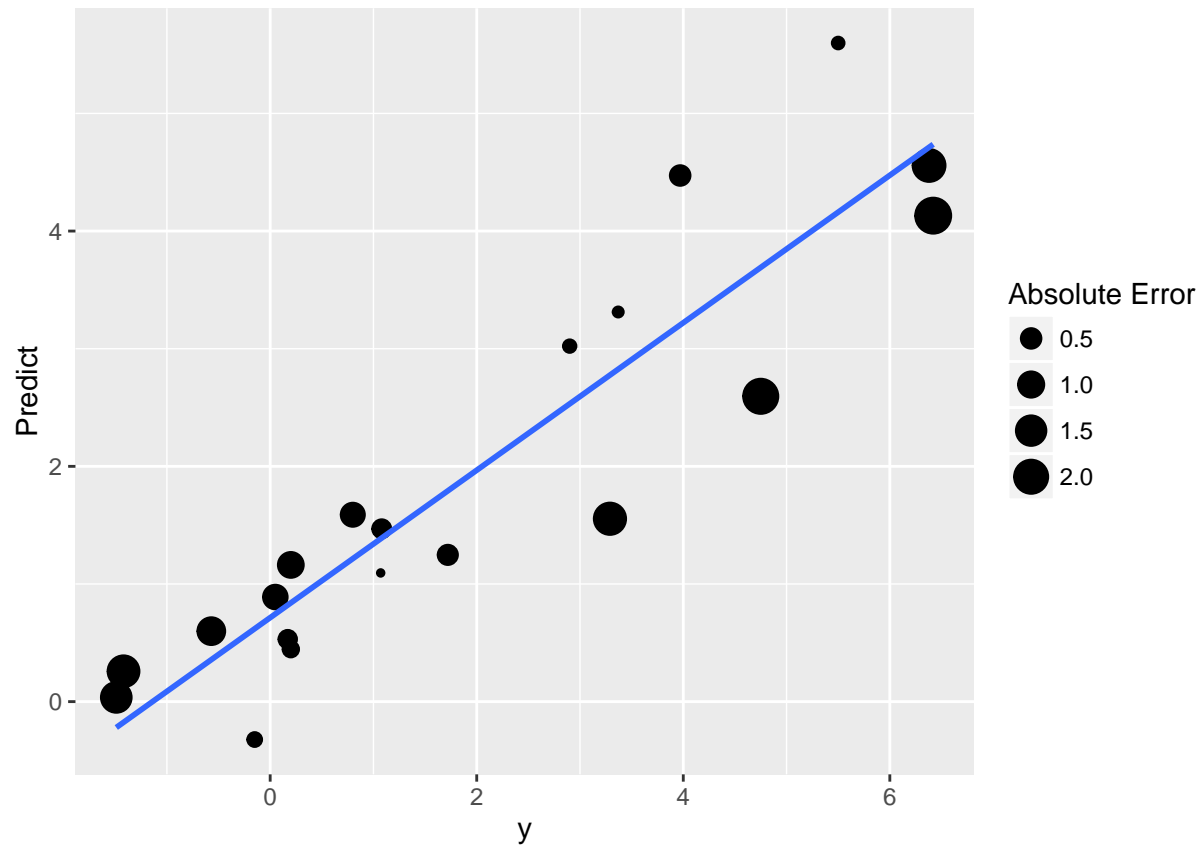
Lasso regression sets alpha=1

```
crossValid <- cv.glmnet(as.matrix(Table1[,1:2]),as.matrix(Table1$y),alpha = 1)
plot(crossValid)
```



```
lambda <- crossValid$lambda.min
sensitivities <- coef(crossValid)
plotDF <- Table1
plotDF[, 'Type'] <- 'Train'
plotDF[, "Predict" ]<- data.frame(Predict=predict(crossValid,as.matrix(Table1[,1:2]),
                                              lambda=lambda))

plotDF$Error <- plotDF$y-plotDF$Predict
ggplot(plotDF,aes(x=y,y=Predict,size=abs(Error))) + geom_point() +
scale_size("Absolute Error") + geom_smooth(method="lm",se=F,size=1)
```



```
sqr( (var(data.frame(plotDF %>% filter(Type=="Train") %>% select(Error))))/20
```

```
##          Error
## Error 0.05832321
```

```
ggplot(plotDF,aes(x=Error)) + geom_histogram()
```



```
sensDF[rowStart:(rowStart + length(sensitivities)-1), 'Method'] <- "Lasso"
sensDF[rowStart:(rowStart+length(sensitivities)-1), 'Var']<-t(t(rownames(sensitivities)))
sensDF[rowStart:(rowStart +length(sensitivities)-1), 'Value']<-as.numeric(sensitivities)
rowStart <- rowStart + length(sensitivities)
```

## Compare Methods

```
ggplot(sensDF, aes(x=reorder(Var, -Value), y=Value, color=Method, group=Method)) +
  geom_point() + geom_line() +
  theme(panel.grid.major = element_blank(),
        axis.text.x = element_text(angle = 90, hjust = 1, size=8))+
  scale_x_discrete("Variable") + scale_y_continuous("Coefficient")
```



The Lasso and Ridge are both more bounded in their coefficients.

## Problem 2

Derive the adjoint operator for the equation

$$-\nabla^2 \phi(x, y, z) + \frac{1}{L^2} \phi(x, y, z) = \frac{Q}{D}$$

$$\phi(0, y, z) = \phi(x, 0, z) = \phi(x, y, 0) = \phi(X, y, z) = \phi(x, Y, z) = \phi(x, y, Z) = C$$

Compute the sensitivity to the QOI:

$$QoI = \int_0^X dx \int_0^Y dy \int_0^Z dz \frac{D}{L^2} \phi(x, y, z)$$

for X,Y,Z,L,, and Q.

### Derive the adjoint operator

Define the operator  $\mathcal{L}$  as

$$\mathcal{L} = \nabla^2 + \frac{1}{L^2}$$

and the adjoint  $\mathcal{L}^\dagger$  as

$$\mathcal{L}^\dagger = \nabla^2 + \frac{1}{L^2}$$

$$\phi^\dagger(0, y, z) = \phi^\dagger(x, 0, z) = \phi^\dagger(x, y, 0) = \phi^\dagger(X, y, z) = \phi^\dagger(x, Y, z) = \phi^\dagger(x, y, Z) = C$$

Setting:

$$\left| \frac{\delta \phi^\dagger}{\delta x} \right|_{x=0} = \left| \frac{\delta \phi}{\delta x} \right|_{x=0}$$

and

$$\left| \frac{\delta \phi^\dagger}{\delta x} \right|_{x=X} = \left| \frac{\delta \phi}{\delta x} \right|_{x=X}$$

and similar for the other two dimensions. Also define the inner product as:

$$(u, v) = \int_0^X dx \int_0^Y dy \int_0^Z dz uv$$

*Proof,* in order to prove that this is an adjoint operator for the above equation, it needs to be shown that  $(\mathcal{L}\phi, \phi^\dagger) = (\phi, \mathcal{L}^\dagger \phi^\dagger)$ .

Equivalent to:

$$\int_0^X dx \int_0^Y dy \int_0^Z dz \left( \phi^\dagger \nabla^2 \phi + \phi^\dagger \frac{\phi}{L^2} \right) = \int_0^X dx \int_0^Y dy \int_0^Z dz \left( \phi \nabla^2 \phi^\dagger + \phi \frac{\phi^\dagger}{L^2} \right) \quad (1)$$

The terms

$$\int_0^X dx \int_0^Y dy \int_0^Z dz \left( \phi^\dagger \frac{\phi}{L^2} \right) = \int_0^X dx \int_0^Y dy \int_0^Z dz \left( \phi \frac{\phi^\dagger}{L^2} \right)$$

are equal. For the other term with,  $\nabla^2$ , we can expand to:

$$\int_0^X dx \int_0^Y dy \int_0^Z dz \left( \phi^\dagger \left[ \frac{\delta^2 \phi}{\delta x^2} + \frac{\delta^2 \phi}{\delta y^2} + \frac{\delta^2 \phi}{\delta z^2} \right] \right)$$

Focusing on the  $x$  terms, noting that  $y$  and  $z$  will have the same derivation. Integration by parts, with  $u = \phi^\dagger$ ,  $du = \frac{\delta\phi^\dagger}{\delta x} dx$ , and  $v = \frac{\delta\phi}{\delta x}$ ,  $dv = \frac{\delta^2\phi}{\delta x^2} dx$  yields.

$$\int_0^Y dy \int_0^Z dz \left( \int_0^X dx \phi^\dagger \frac{\delta^2\phi}{\delta x^2} \right) = \int_0^Y dy \int_0^Z dz \left( \left[ \phi^\dagger \frac{\delta\phi}{\delta x} \right]_{x=0}^{x=X} - \int_0^X dx \frac{\delta\phi}{\delta x} \frac{\delta\phi^\dagger}{\delta x} dx \right)$$

Performing another integration by parts, with  $u = \frac{\delta\phi^\dagger}{\delta x}$ ,  $du = \frac{\delta^2\phi^\dagger}{\delta x^2} dx$  and,  $v = \phi$ ,  $dv = \frac{\delta\phi}{\delta x} dx$ .

$$= \int_0^Y dy \int_0^Z dz \left( \left[ \phi^\dagger \frac{\delta\phi}{\delta x} \right]_{x=0}^{x=X} - \left[ \phi \frac{\delta\phi^\dagger}{\delta x} \right]_{x=0}^{x=X} + \int_0^X dx \phi \frac{\delta^2\phi^\dagger}{\delta x^2} dx \right)$$

At the boundaries, both  $\phi$  and  $\phi^\dagger$  are a constant, and the derivatives of both at the boundaries are equal, and therefore those terms cancel, leaving

$$\int_0^Y dy \int_0^Z dz \left( \int_0^X dx \phi \frac{\delta^2\phi^\dagger}{\delta x^2} dx \right)$$

which is equal to the  $x$  component of the  $\nabla^2$  term of the RHS of equation 1 above.

### Compute the sensitivity to the QoI:

I don't know if this is the right way to go about this, but if you modify the first equation listed in this problem to:

$$\phi = L^2 \left[ \frac{Q}{D} + \nabla^2 \phi \right]$$

and use it as a substitution, then we get something like this,

$$\begin{aligned} \text{QoI} &= \int_0^X dx \int_0^Y dy \int_0^Z dz \frac{D}{L^2} \phi \\ &= \int_0^X dx \int_0^Y dy \int_0^Z dz \frac{D}{L^2} \left( L^2 \left[ \frac{Q}{D} + \nabla^2 \phi \right] \right) \\ &= \int_0^X dx \int_0^Y dy \int_0^Z dz [Q + D \nabla^2 \phi] \end{aligned}$$

If  $Q$  and  $D$  both are independent of space, then

$$\text{QoI} = QXYZ + D \left[ \int_0^Y dy \int_0^Z dz \left[ \frac{\delta\phi}{\delta x} \right]_{x=0}^{x=X} + \int_0^X dx \int_0^Z dz \left[ \frac{\delta\phi}{\delta y} \right]_{y=0}^{y=Y} + \int_0^X dx \int_0^Y dy \left[ \frac{\delta\phi}{\delta z} \right]_{z=0}^{z=Z} \right]$$

I'm not sure how the adjoint helps me though.

## Problem 3

For the random variable  $X \sim N(0,1)$  draw fifty samples and generate histograms using the following sampling techniques

- (a) Simple random sampling
- (b) Stratified sampling
- (c) A van der Corput sequence of base 2
- (d) A van der Corput sequence of base 3

Simple random sampling samples  $U(0,1)$  and plugs this value into the inverse CDF. Stratified sampling separates  $U(0,1)$  into equal bins and samples “Randomly” in each bin. Van der Corput sequences divides an interval into a number of equal subintervals.

For example, the ordinary van der Corput sequence in base 3 is given by  $1/3, 2/3, 1/9, 4/9, 7/9, 2/9, 5/9, 8/9, 1/27$ .

Listing 1: Script for Problem

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

#####
##### Import packages #####
5 #####

import numpy as np
import matplotlib.pyplot as plt
import time
10 start_time = time.time()
from scipy.stats import norm

#####
##### Functions #####
15 #####

#Van der Corput sequence function found online
def vdc(n, base=2):
    vdc, denom = 0,1
20     while n:
        denom *= base
        n, remainder = divmod(n, base)
        vdc += remainder / denom
    return vdc
25

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

30 #Make sure Nstrata <= N

N=50 #samples
```



```

Nbins=15  #hist plot
Nstrata=49
35 filename="V2Norm.pdf"
   #Stratified or Normal or Van der Corput
Xlabel="Van der Corput Sampling with base=2"
RandomNumbers=[]
vanBase=2;van=True

40
   #Sampling for normal and stratified
   if not van:
       Nloop=int(N/Nstrata)*Nstrata
       for i in range(0,int(N/Nstrata)):
45           for j in range(0,Nstrata):
               RandomNumbers.append(np.random.uniform(low=j/Nstrata,
                                                           high=(j+1)/Nstrata,size=1))

               #If N/Nstrata doesn't divide evenly
               if Nloop<N:
50                   for j in range(0,N-Nloop):
                       RandomNumbers.append(np.random.uniform(low=j/Nstrata,
                                                                   high=(j+1)/Nstrata,size=1))

   #Sampling for van
   if van:
55       for i in range(0,N):
           RandomNumbers.append(vdc(i+1,vanBase))

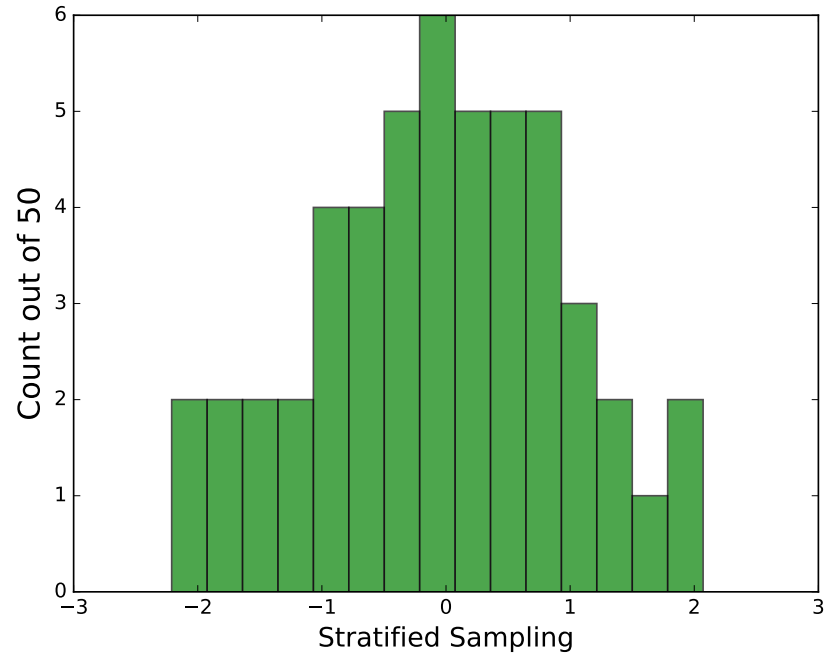
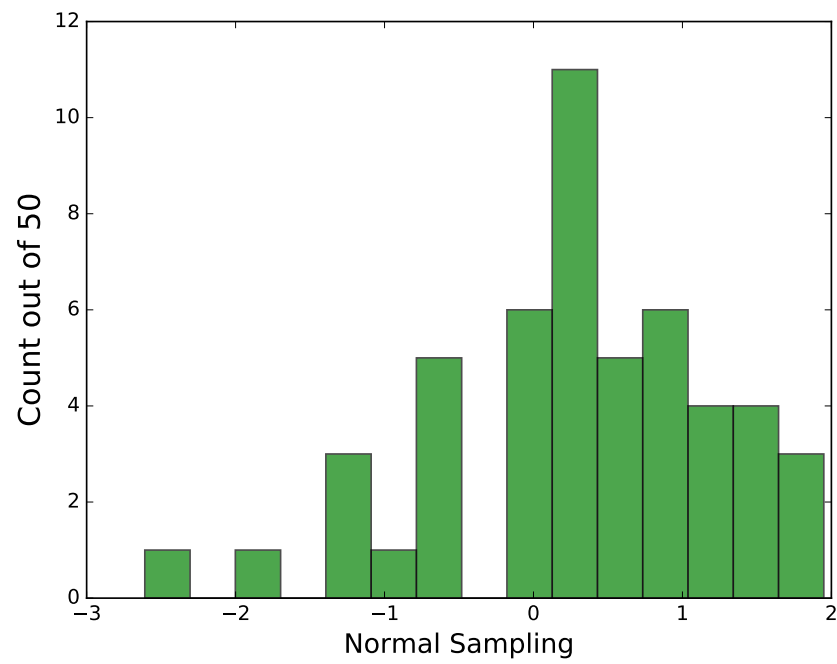
   #Sample the inverse of the CDF of the standard normal
   #distribution
60 Samples=norm.ppf(RandomNumbers)

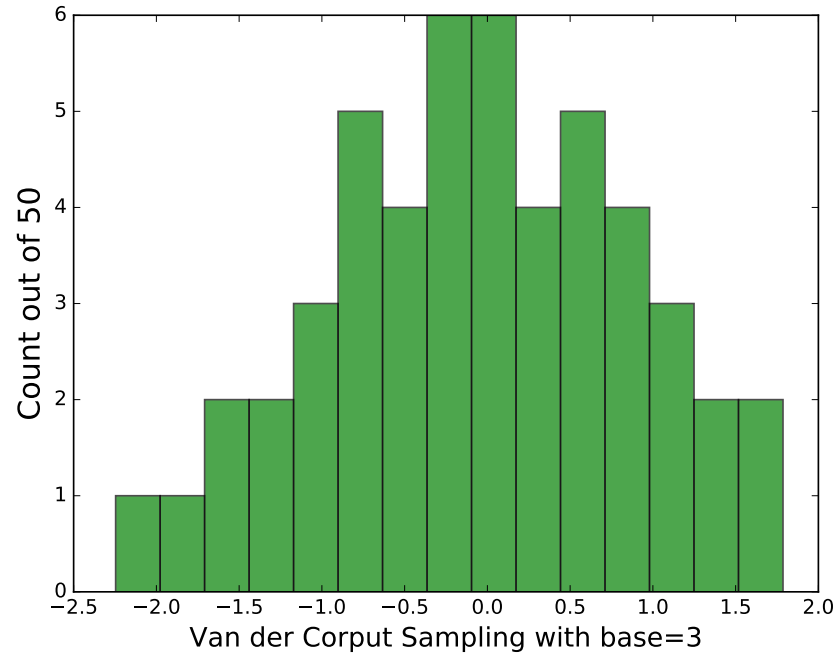
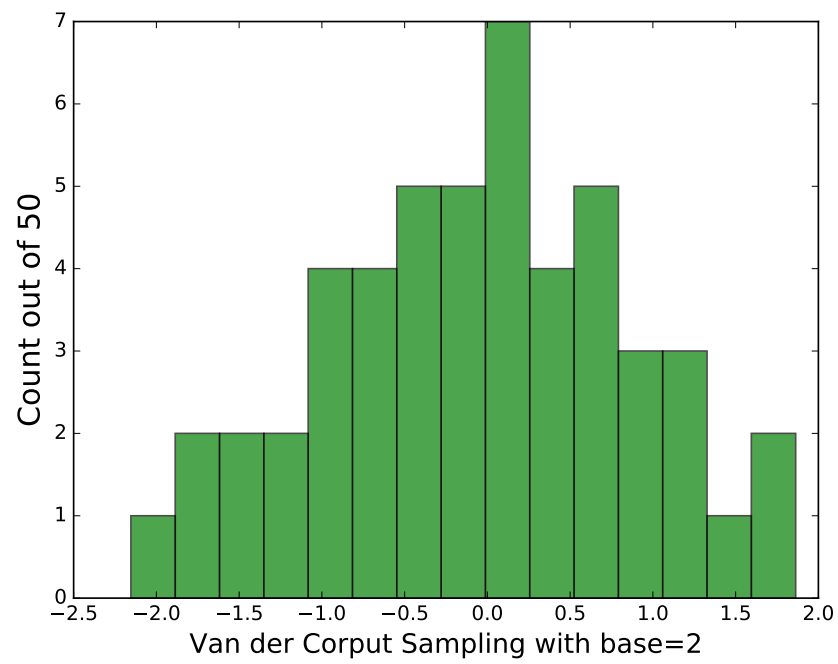
   #Generate histogram
   fig=plt.figure()
   ax=fig.add_subplot(111)
65 ax.set_xlabel(Xlabel,fontsize=16)
   ax.set_ylabel('Count out of '+str(N),fontsize=18)
   ax.hist(Samples,Nbins,color='green',alpha=0.7,edgecolor='black')
   #ax.set_xlim(-500,500)
   plt.savefig(filename)

70
   ##### Time To execute #####

   print("--- %s seconds ---" % (time.time() - start_time))

```





## Problem 4

Consider the Rosenbrock function  $f(x, y) = (1 - x)^2 + 100(y - x^2)^2$ . Assume that  $x = 2t - 1$ , where  $T \sim B(3, 2)$  and  $y = 2s - 1$ , where  $S \sim B(1.1, 2)$ . Estimate the probability that  $f(x, y)$  is less than 10 using:

- (a) a first-order second-moment reliability method
- (b) Latin hypercube sampling using 50 points
- (c) A Halton sequence using 50 points

Compare this with the probability you calculate using  $10^5$  random samples. (*Hint: Matlab has a built-in function for sampling beta R.V.'s "betard"*).

### A first-order second-moment reliability method

Will use a gaussian approximation as shown in section 7.3 in the course notes (FORM).

In this method the performance function ( $Z(x, y)$ ) is a function of the random variables  $x$  and  $y$ , and is defined such that the failure surface is the location where  $Z = 0$  (top of page 119 Ch 7) such that  $Z < 0$  represents failure and  $Z > 0$  represents success. For the case above, this would mean that our performance function is:

$$\begin{aligned} Z &= 10 - f(x, y) \\ &= 10 - (1 - x)^2 + 100(y - x^2)^2 \end{aligned}$$

Next, the probability of failure is defined as:

$$p_{fail} = 1 - \Phi\left(\frac{\mu_Z}{\sigma_Z}\right)$$

Where  $\Phi$  is the CDF for a standard normal,  $\mu_Z$  and  $\sigma_Z$  are the mean and standard deviation of  $Z$ . As a reminder, if  $Z$  were a standard normal, defined such that any part of  $Z$  that is less than 0 is failure. Then because  $\mu_Z = 0$  there would be a 50% chance of failure. If  $Z$  were a non standard normal, then the distance from zero would be normalized (by dividing by  $\sigma_Z$ ) to units of  $\sigma$ , and as  $\mu_Z$  increases, the chance of failure would continue to decrease, which make sense, as the mean of the performance function moves further and further away from the failure point ( $Z = 0$ ), the probability of failure decreases.

I am trying to spell this out for myself, because I was really confused about this. There are two things I would like to point out to future self. First,  $Z$  may not be normal, which is why this method is only exact if  $Z$  is normal, otherwise its an approximation. Second, if  $\mu_Z$  were less than 0, then the equation for the probability of failure should (I think) change to

$$p_{fail} = 0.5 + \Phi\left(\frac{|\mu_Z|}{\sigma_Z}\right)$$

Also third, I am not sure if  $Z$  has to be a typical PDF or CDF, will let you know after I do some of the math McClarren gave.

The mean for  $Z$  was defined as

$$\mu_Z \approx g(\mu_{x,y})$$

where  $g$  is the function we defined as  $Z$  (first part of the Taylor expansion of  $Z$ ) evaluated at the mean values of  $x$  and  $y$ . The standard deviation of  $Z$  was defined as the the second part of the Taylor expansion of  $Z$  (without covariances because we are going to assume that all random variables are independent), namely

$$\sigma_Z^2 = \left( \left| \frac{\delta g}{\delta x} \right|_{\mu_x} \sigma_x \right)^2 + \left( \left| \frac{\delta g}{\delta y} \right|_{\mu_y} \sigma_y \right)^2$$

For what I defined as  $Z$  above,

$$\begin{aligned} \frac{\delta g}{\delta x} &= -2(x-1) - 400x(x^2 - y) \\ \frac{\delta g}{\delta y} &= -200(y - x^2) \end{aligned}$$

Also for a beta R.V

$$\begin{aligned} \mu &= \frac{a}{a+b} \\ \sigma^2 &= \frac{ab}{(a+b)^2(a+b+1)} \end{aligned}$$

### Calculations

For the random variable  $t$  used in  $x = 2t - 1$

mean

$$\mu_t = \frac{3}{3+2} = \mathbf{0.6}$$

$$\mu_x = 2 * \mathbf{0.6} - 1 = \boxed{0.2}$$

standard deviation

$$\sigma_t^2 = \frac{3 \cdot 2}{(3+2)^2(3+2+1)} = \mathbf{0.04}$$

$$\begin{aligned} \sigma_x^2 &= \left| \frac{\delta x}{\delta t} \right|_{\mu_T}^2 \sigma_t^2 \\ &= 2^2 \cdot \mathbf{0.04} = \boxed{0.16} \end{aligned}$$

For the random variable  $s$  used in  $y = 2s - 1$

mean

$$\mu_s = \frac{1.1}{1.1 + 2} = \mathbf{0.354839}$$

$$\mu_y = 2 * \mathbf{0.354839} - 1 = \boxed{-0.290323}$$

standard deviation

$$\sigma_s^2 = \frac{1.1 \cdot 2}{(1.1 + 2)^2(1.1 + 2 + 1)} = \mathbf{0.055836}$$

$$\sigma_y^2 = \left| \frac{\delta y}{\delta s} \right|_{\mu_s}^2 \sigma_s^2$$

$$= 2^2 \cdot \mathbf{0.055836} = \boxed{0.223345}$$

For the partial derivative terms

$$\left| \frac{\delta g}{\delta x} \right|_{\mu_x} = -2(x - 1) - 400x(x^2 - y) = -2(0.2 - 1) - 400 \cdot 2(0.2^2 - (-0.290323)) = \boxed{-24.8258}$$

$$\left| \frac{\delta g}{\delta y} \right|_{\mu_y} = -200(y - x^2) = -200(-0.290323 - 0.2^2) = \boxed{66.0646}$$

For  $Z$  and the probability of failure

$$\mu_Z = 10 - (1 - 0.2)^2 + 100(-0.290323 - 0.2^2)^2 = \boxed{20.2713}$$

$$\sigma_Z^2 = 24.8^2 \cdot 0.16 + 66.0646^2 \cdot 0.223345 = 1073.41$$

$$\sigma_Z = \boxed{32.7629}$$

$$p_{fail} = 1 - \Phi\left(\frac{20.27}{32.7629}\right)$$

$$= \boxed{0.268}$$

Listing 2: Script for Hypercube and Halton

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

#####
##### Import packages #####
5 #####

import time
start_time = time.time()
import Functions as fun
10 import lhsmdu
```

```

from random import shuffle

#####
##### Calculations #####
15 #####

N=100000 #Samples
Nbins=30 #Hist Plot
Nstrata=10
20 filename="NormalStrat.pdf"

Xlabel="Normal Sampling"
RandomNumbersX=fun.np.random.uniform(0,1,N)
RandomNumbersY=fun.np.random.uniform(0,1,N)
25 #RandomNumbersX=fun.Rstrat(N,Nstrata) #strat sampling
#RandomNumbersY=fun.Rstrat(N,Nstrata)
#l=lhsmdu.sample(2,N) #Hyper cube sampling
#RandomNumbersX=l[0].A1
#RandomNumbersY=l[1].A1
30 #RandomNumbersX=fun.Rvdc(N,7) #Halton sequence
#RandomNumbersY=fun.Rvdc(N,7) #shuffled the list
#shuffle(RandomNumbersX)
#shuffle(RandomNumbersY)

35 Samplest=fun.beta.ppf(RandomNumbersX,3,2)
Sampless=fun.beta.ppf(RandomNumbersY,1.1,2)

X=fun.X(Samplest)
Y=fun.Y(Sampless)
40 f=fun.Rosen(X,Y)

#Plot the data for Rosenbrok, and plot fitted PDF
Xlabel="Rosenbrock Function Histogram"
45 (n,bins,ax,fig)=fun.HIST(Xlabel,f,Nbins,N)
(ax,fig)=fun.HISTDataToPDF(n,bins,ax,fig)
fun.plt.savefig(filename)

#Find the probability of f being less than 10
50 PGreater=sum(i<10 for i in f)/N

print("The probability of being less than 10 is: "+str(PGreater))

55

##### Time To execute #####

print("--- %s seconds ---" % (time.time() - start_time))

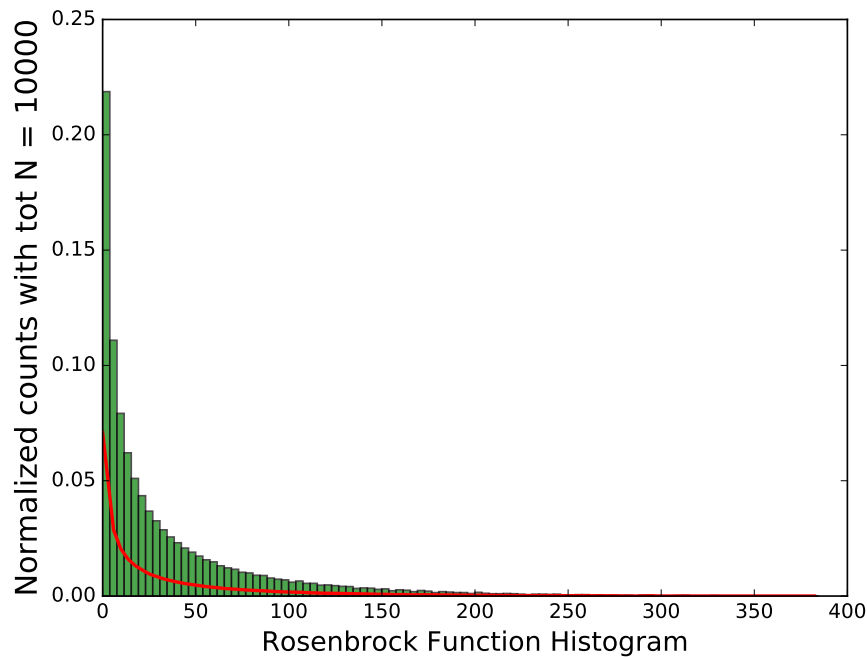
```

My PDF integrates to 1.01, which I'm okay with. The table below summarizes my results.

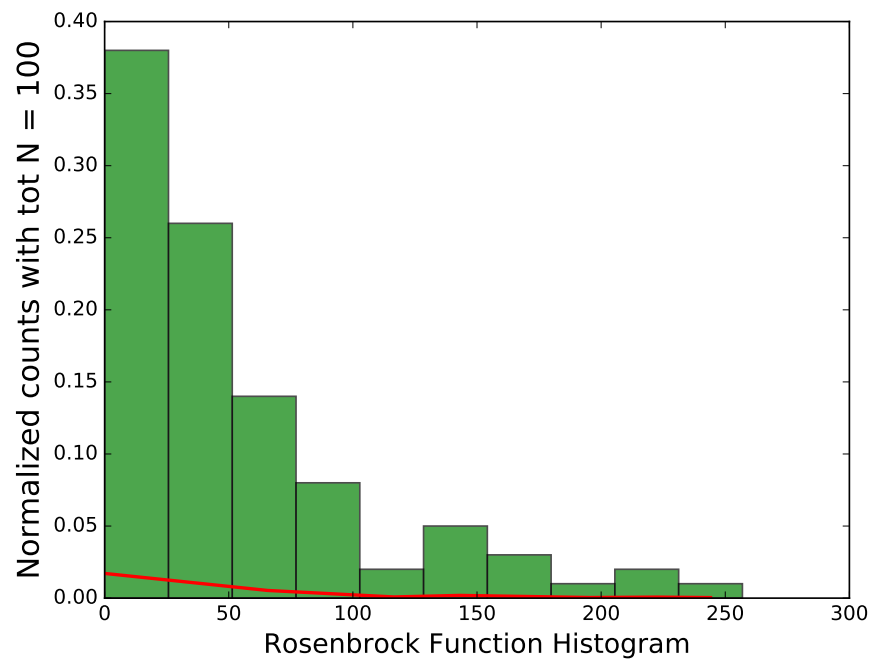
Table 2: Different Sampling Techniques

Method	$p_{fail}$ 50 points	$p_{fail}$ 100 points
Stratified	0.30	0.28
First Order	0.268	
Latin Hyper	0.36	0.26
Halton	0.26	0.28
Normal ( $10^5$ )	0.26017	

It should be noted that I shuffled the stratified samples and the halton samples as well, because otherwise there would be some correlation between the numbers. The first order listing in the table is not from the code, but the calculation above, and did not use 50 points.







## Problem 5

Consider the exponential integral function,  $E_n(x)$ ,

$$E_n(x) = \int_1^\infty \frac{e^{-xt}}{t^n} dt$$

This function is involved in the solution to many pure-absorbing transport problems. Use this function to solve the transport problem,

$$\mu \frac{\delta \psi}{\delta x} + \sigma \psi = 0,$$

$$\psi(0, \mu > 0) = 1, \psi(10, \mu < 0) = 0,$$

for the scalar flux  $\phi(x) = \int_{-1}^1 \psi(x, \mu) d\mu$ . Assume that  $\sigma \sim \text{GAM}(10, 0.1)$ . Use a PCE expansion to estimate the distribution, mean, and variance of  $\phi(x)$  at  $x = 1, 1.5, 3, 5$ . Also, plot the mean value of  $\phi$  as a function of  $x$ .

Using the integrating factor approach we proceed as follows:

$$\begin{aligned} \frac{\delta \psi}{\delta x} + \frac{\sigma \psi}{\mu} &= 0 \\ \frac{\delta}{\delta x} \left[ e^{\frac{\sigma x}{\mu}} \psi \right] &= 0 \end{aligned}$$

Integrating from 0 to  $x$  for  $\mu > 0$ , we obtain (yes I am copying some old notes)

$$\begin{aligned} \psi(x, \mu > 0) e^{\frac{\sigma x}{\mu}} - \psi(0, \mu > 0) e^{\frac{\sigma \cdot 0}{\mu}} &= 0 \\ \psi(x, \mu > 0) e^{\frac{\sigma x}{\mu}} - 1 &= 0 \\ \psi(x, \mu > 0) e^{\frac{\sigma x}{\mu}} &= 1 \\ \psi(x, \mu > 0) &= e^{-\frac{\sigma x}{\mu}} \end{aligned}$$

Integrating from  $x$  to 10 for  $\mu < 0$ , we obtain

$$\begin{aligned} \psi(10, \mu < 0) e^{\frac{\sigma 10}{\mu}} - \psi(x, \mu < 0) e^{\frac{\sigma x}{\mu}} &= 0 \\ -\psi(x, \mu < 0) e^{\frac{\sigma x}{\mu}} &= 0 \\ \psi(x, \mu < 0) &= 0 \end{aligned}$$

Here we can note that there is no flux traveling to the left, and will focus on the flux traveling to the right. Integrating over all  $\mu > 0$ , and using a substitution of  $z = 1/\mu$  and  $d\mu = -z^{-2}$ :

$$\begin{aligned}
\phi^+(x) &= 2\pi \int_0^1 \psi(x, \mu < 0) d\mu \\
&= 2\pi \int_0^1 e^{-\frac{\sigma x}{\mu}} d\mu \\
&= 2\pi \int_{\infty}^1 -\frac{e^{-\sigma x z}}{z^2} \\
&= 2\pi \int_1^{\infty} \frac{e^{-\sigma x z}}{z^2} \\
&= 2\pi E_2(\sigma x)
\end{aligned}$$

I think this might help later on, if we define  $\phi$  like:

$$\phi^+(x') = 2\pi E_2(x')$$

where  $x' = \sigma x$ .

Now to use PCE expansion to estimate the distribution, mean, and variance of  $\phi(x)$ . First off, I want to say that I have no idea what's going on. Next, because we have a gamma distribution, I suppose we should use Laguerre Polynomials. Where:

$$\phi(x') = \sum_{n=0}^{\infty} c_n L_n^{(\alpha)}(\beta x')$$

and

$$c_n = \frac{n!}{\Gamma(n + \alpha + 1)} \int_0^{\infty} \phi\left(\frac{z}{\beta}\right) z^{\alpha} e^{-z} L_n^{(\alpha)}(z) dz$$

In order to estimate the coefficients in the expansion we have to evaluate a wonderful integral. In order to estimate the integral, will use Gauss-Laguerre quadrature (like I have any idea what that is) to have as few evaluations of the integrand as possible.

The quadrature rule has the form

$$\int_0^{\infty} f(z) z^{\alpha} e^{-z} dz \approx \sum_{i=1}^n w_i f(z_i)$$

Where  $z_i$  are the  $n$  roots of  $L_n^{(\alpha)}(z)$ , and the weights are given by:

$$w_i = \frac{\Gamma(n + \alpha) z_i}{n!(n + \alpha)(L_{n-1}^{(\alpha)}(z_i))^2}$$

Looking at the quadrature rule, I think  $f(z)$ , in our instance would have to be

$$f(z) = \phi\left(\frac{z}{\beta}\right) L_n^{(\alpha)}(z)$$

I hope this is correct, if not then the only person I can blame is myself. The notes aren't very clear on what  $f(z)$  is. If I am correct, then the  $c_n$  constants are:

$$c_n \approx \frac{n!}{\Gamma(n + \alpha + 1)} \sum_{i=1}^n w_i f(z_i)$$

According to the notes, the variance is:

$$\text{Var}(G) = \sum_{n=1}^{\infty} \frac{\Gamma(n + \alpha + 1)}{\Gamma(\alpha + 1)n!} c_n^2$$

And  $c_0$  is:

$$c_0 = \int_0^\infty \phi\left(\frac{z}{\beta}\right) \frac{z^\alpha e^{-z}}{\Gamma(\alpha+1)} dz = E[g(X)]$$

I am not sure how to get this other than sampling.

Listing 3: Script for problem

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

#####
##### Import packages #####
5 #####

import time
start_time = time.time()
import Functions as fun
10 import lhsmdu
from mpmath import expint

#####
##### Calculations #####
15 #####

N=1000 #Samples
Nbins=60 #Hist Plot
Nstrata=10
20 filename="mean2.pdf"

#RandomNumbers=fun.np.random.uniform(0,1,N)
#RandomNumbers=fun.Rstrat(N,Nstrata) #strat sampling
#l=lhsmdu.sample(1,N) #Hyper cube sampling
25 #RandomNumbers=l[0].A1
#RandomNumbers=fun.Rvdc(N,7) #Halton sequence

#SamplesSigma=fun.gamma.ppf(RandomNumbers,0.1,10)
SamplesSigma=fun.np.random.gamma(shape=10,scale=0.1,size=N)
30
x=1
phi=[]
for i in range(0,len(SamplesSigma)):
    E2=expint(2,SamplesSigma[i]*x)
35 phi.append(float(2*fun.np.pi*E2))

#Plot the data, and plot fitted PDF
Xlabel="Distribution of flux"
(n,bins,ax,fig)=fun.HIST(Xlabel,phi,Nbins,N)
40 (ax,fig)=fun.HISTDataToPDF(n,bins,ax,fig)
fun.plt.savefig(filename)

##### Time To execute #####
45
print("--- %s seconds ---" % (time.time() - start_time))
```

Table 3: Different Sampling Techniques

Location	Distribution	Mean	Variance
1	Dist	mean	Variance
1.5	Dist	mean	Variance
3	Dist	mean	Variance
5	Dist	mean	Variance

