### PS4

## Güneykan Özgül

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# 1 Analytical Estimation of Variance

Let's try to estimate  $\sigma_I$  analytically for one segment.

$$\sigma_I^2 = \left\langle \frac{f^2}{w^2} \right\rangle - \left\langle \frac{f}{w} \right\rangle^2$$

Let  $g = \frac{f}{w}$ , then,

$$\sigma_{f/w}^2 = \langle g^2 \rangle - \langle g \rangle^2$$

We can expand g using Taylor Series around  $\frac{b+a}{2}$ ,

$$g(x) = g\left(\frac{b+a}{2}\right) + g'\left(\frac{b+a}{2}\right)\left(x - \frac{b+a}{2}\right) + \frac{1}{2}g''\left(\frac{b+a}{2}\right)\left(x - \frac{b+a}{2}\right)^2$$

We can also approximate first and second derivative very accurately for a small region,

$$g'\left(\frac{b+a}{2}\right) = \frac{g(b) - g(a)}{b-a}$$
$$g''\left(\frac{b+a}{2}\right) = \frac{g(b) - 2g(\frac{b+a}{2}) + g(a)}{(\frac{b-a}{2})^2}$$

To simplify equations we can define the following variables,

$$p = g(\frac{b+a}{2})$$

$$q = \frac{g(b) - g(a)}{b - a}$$

$$r = \frac{g(b) - 2g(\frac{b+a}{2}) + g(a)}{2(\frac{b-a}{2})^2}$$

$$u = (x - \frac{b+a}{2})$$

Then,

N	I	$\sigma_I$	$\sigma_{analytical}/\sigma_{experiment}$
$10^{2}$	-0.121168988625	0.000830959217088	1.03652094663
$10^{3}$	-0.120463231735	0.000278923898527	0.976499590964
$10^{4}$	-0.119894524822	8.62560747757e-05	0.998546057823
$10^{5}$	-0.120008293845	2.7295876215e-05	0.9978396394
$10^{6}$	-0.120011109322	8.63024146321e-06	0.998009891122

$$g(x) = ru^2 + qu + p$$

Since we forced w to be equal to f at the boundaries, q is 0. Our job reduces to calculate

$$\langle (ru^2+p)^2 \rangle - \langle ru^2+p \rangle^2$$

Expanding the terms,

$$\begin{split} \sigma_{f/w}^2 &= \left\langle r^2 u^4 + 2rpu^2 + p^2 \right\rangle - \left\langle ru^2 + p \right\rangle^2 \\ &= \left( r^2 \left\langle u^4 \right\rangle + 2rp \left\langle u^2 \right\rangle + p^2 \right) - \left( r^2 \left\langle u^2 \right\rangle^2 + 2rp \left\langle u^2 \right\rangle + p^2 \right) \\ &= r^2 \left\langle u^4 \right\rangle - r^2 \left\langle u^2 \right\rangle^2 \\ &= r^2 (\left\langle u^4 \right\rangle - \left\langle u^2 \right\rangle^2) \end{split}$$

This could further be simplified as,

$$\sigma_{f/w}^2 = r^2 \sigma_{u^2}^2$$

Finally  $\sigma_I$  can be estimated as,

$$\sigma_I = \frac{(b-a)}{\sqrt{N}} r \sigma_{u^2} = \frac{(b-a)}{\sqrt{N}} \frac{g(b) - 2g(\frac{b+a}{2}) + g(a)}{2(\frac{b-a}{2})^2} \sqrt{\left(\frac{2(b-a)^4}{5 \cdot 2^5} - \frac{4(b-a)^4}{9 \cdot 2^6}\right)}$$

$$\sigma_I = \sqrt{\left(\frac{2(b-a)^2}{5 \cdot 2^5} - \frac{4(b-a)^2}{9 \cdot 2^6}\right)} \frac{2}{\sqrt{N}} (g(b) - 2g(\frac{b+a}{2}) + g(a))$$
or
$$\sigma_I = \frac{0.03727(b-a)^3}{\sqrt{N}} g''\left(\frac{a+b}{2}\right)$$

# 2 Appendix

```
import numpy as np
from numpy. polynomial import Polynomial as P
#import plotly
#import plotly plotly as py
#import plotly.figure_factory as ff
import matplotlib.pyplot as plt
#Integrand function
def f(x,H):
     return (x-5)*np.exp(-(x/2-3))+H
#Calculates the coefficients of linear weight function.
def findw (f, H, lower, upper, normalize):
    #Find the linear function.
    slope = (f(upper, H) - f(lower, H)) / (upper-lower)
    a=slope
    b=-slope*upper+f(upper,H)
    #Normalization.
    A=(a/2)*(upper**2)+b*upper-(a/2)*(lower**2)-b*lower
    if normalize:
         a/=A
         b/=A
     return [a,b]
#Performs integration.
def integrate (f, lower, upper, N, C):
    w=findw(f,H,lower,upper,True)
    #Generate uniform random inputs.
    inputs=np.random.rand(N)
    a=w[0]/2
    b=w[1]
    c=-(a*lower**2+b*lower)
    SUM=0
    SUM2=0
    inverse\_inputs = []
     for i in inputs:
         p = [(-b - np. \, s\, q\, r\, t\, (\, b**2 - 4*a\, *(\, c-i\, )\, )\, )\, /\, (\, 2*a\, )\, , (\, -b + np. \, s\, q\, r\, t\, (\, b**2 - 4*a\, *(\, c-i\, )\, )\, )\, /\, (\, 2*a\, )\, ]
         if p[0] >= lower and p[0] <= upper:
              inverse_inputs.append(p[0])
              inverse_inputs.append(p[1])
     inverse_inputs=np.array(inverse_inputs)
```

```
\#Calculate f(inverse(x))/w(inverse(x)).
   outputsF=f(inverse_inputs,H)
   outputsW=w[0]*(inverse_inputs)+w[1]
   outputs=outputsF/outputsW
   SUM=outputs.sum()
   SUM2=(outputs*outputs).sum()
   var=SUM2/N-(SUM/N)**2
    var=var/N
   #Store generated points for variance calculation.
   Vsum=outputs.sum()
    return Vsum/N-H*(upper-lower),(upper-lower)**2*var
def theoretical_sigma(f,lower,upper,N,C):
   w=findw(f,C,lower,upper,True)
    flower=f(lower,C)
    fmiddle=f((lower+upper)/2,C)
    fupper=f (upper,C)
    wlower=w[0]*lower+w[1]
    wmiddle=w[0]*(lower+upper)/2+w[1]
   wupper=w[0]*upper+w[1]
    gupper=fupper/wupper
    gmiddle=fmiddle/wmiddle
    glower=flower/wlower
   #return (upper-lower)*np.sqrt(var)
   return sigma
low = 4.6
up=5.2
#Divide the region into 10 pieces.
l = [low, up]
#Real value of the integral
I_real = -.12002
#N values
N = [100, 1000, 10000, 100000, 1000000]
```

```
 \#Integration\ results. \\ results = [] \\ \#Standart\ deviation\ values \\ sigmas = [] \\ for\ k\ in\ N: \\ I = 0 \\ sigma = 0 \\ S = 1000 \\ for\ i\ in\ range\ (0\,,len\,(1)\,-1): \\ temp\,,temp\,2 = integrate\,(f\,,l\,[i\,]\,,l\,[i\,+1]\,,k\,,S) \\ I + = temp \\ sigma + = temp\,2 \\ results\,.append\,(I) \\ sigmas\,.append\,(np\,.sqrt\,(sigma)) \\ print\,(k\,,I\,,I-I\_real\,,np\,.sqrt\,(sigma)\,,theoretical\_sigma\,(f\,,low\,,up\,,k\,,S)/np\,.sqrt\,(sigma)) \\ print\,(k\,,I\,,I-I\_real\,,np\,.sqrt\,(sigma)\,,theoretical\_sigma\,(f\,,low\,,up\,,k\,,S)/np\,.sqrt\,(sigma), \\ \end{tabular}
```