

**Problem 1:**

```
##Import these packages:
import math
import pandas
import numpy as np
import scipy.stats
from scipy.stats import uniform
from scipy.stats import binom
import math
from scipy.stats import norm
import matplotlib
import matplotlib.pyplot as plt
```

**Python Code:**

```
#####Problem 1#####
x = binom.rvs(0, 0.3, size=1000) // generates random variates from a binomial distribution with X=0, pmf = 0.3
y = binom.rvs(1, 0.2, size=1000) /// generates random variates from a binomial distribution with X=1, pmf = 0.2
z = binom.rvs(3, 0.5, size=1000) /// generates random variates from a binomial distribution with X=3, pmf = 0.5
print(x)
print(y)
print(z)
#####Problem 1#####
# for inline plots in jupyter
%matplotlib inline
# import matplotlib
import matplotlib.pyplot as plt
# import seaborn
import seaborn as sns
# settings for seaborn plotting style
sns.set(color_codes=True)
# settings for seaborn plot sizes
sns.set(rc={'figure.figsize':(4.5,3)})
data_binom_0 = binom.rvs(n=0,p=0.3, size=1000)
print(data_binom_0)
```



## Problem 2:

The Box-Muller transform is a method for generating normally distributed random numbers from uniformly distributed random numbers. The Box-Muller transformation can be summarized as follows, suppose  $u_1$  and  $u_2$  are independent random variables that are uniformly distributed between 0 and 1 and let then  $z_1$  and  $z_2$  are independent random variables with a standard normal distribution. Intuitively, the transformation maps each circle of points around the origin to another circle of points around the origin where larger outer circles are mapped to closely-spaced inner circles and inner circles to outer circles.

### Python Code:

```
#####Problem 2#####

def box_muller():

    u1 = random.random()

    u2 = random.random()

    t = math.sqrt((-2) * math.log(u1))

    v = 2 * math.pi * u2

    return t * math.cos(v), t * math.sin(v)

from numpy import random, sqrt, log, sin, cos, pi

from pylab import show,hist,subplot,figure

# transformation function
def gaussian(u1,u2):

    z1 = sqrt(-2*log(u1))*cos(2*pi*u2)

    z2 = sqrt(-2*log(u1))*sin(2*pi*u2)

    return z1,z2

# uniformly distributed values between 0 and 1
u1 = random.rand(1000)
u2 = random.rand(1000)

# run the transformation
z1,z2 = gaussian(u1,u2)

# plotting the values before and after the transformation
figure()

subplot(221) # the first row of graphs

hist(u1) # contains the histograms of u1 and u2

subplot(222)

hist(u2)
```

```
subplot(223) # the second contains
```

```
hist(z1) # the histograms of z1 and z2
```

```
subplot(224)
```

```
hist(z2)
```

```
show()
```

```
#####Problem 2#####
```

```
##Random number generation with Box-Muller algorithm
```

```
import math
```

```
import random
```

```
import sys
```

```
import traceback
```

```
class RndnumBoxMuller:
```

```
    M = 10 # Average
```

```
    S = 2.5 # Standard deviation
```

```
    N = 10000 # Number to generate
```

```
    SCALE = N // 100 # Scale for histogram
```

```
    def __init__(self):
```

```
        self.hist = [0 for _ in range(self.M * 5)]
```

```
    def generate_rndnum(self):
```

```
        ##Generation of random nos.
```

```
        try:
```

```
            for _ in range(self.N):
```

```
                res = self.__rnd()
```

```
                self.hist[res[0]] += 1
```

```
                self.hist[res[1]] += 1
```

```
        except Exception as e:
```

```
            raise
```

```
    def display(self):
```

```
        ##showing
```

```
        try:
```

```
            for i in range(0, self.M * 2 + 1):
```

```
                print("{:>3}:{:>4} | ".format(i, self.hist[i]), end="")
```

```
                for j in range(1, self.hist[i] // self.SCALE + 1):
```

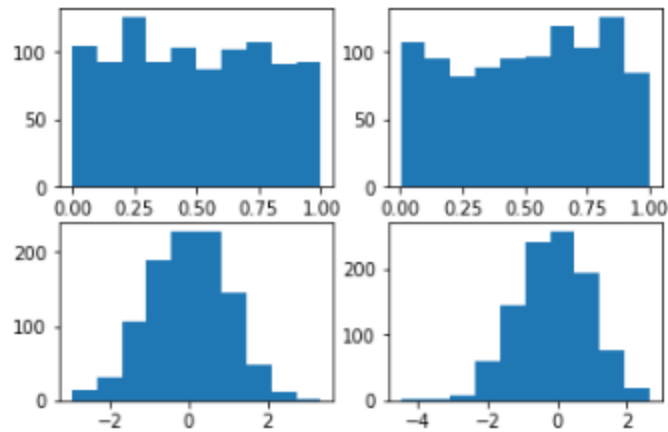
```
                    print("*", end="")
```

```

        print()
    except Exception as e:
        raise
def __rnd(self):
##random integers generation.
    try:
        r_1 = random.random()
        r_2 = random.random()
        x = self.S \
            * math.sqrt(-2 * math.log(r_1)) \
            * math.cos(2 * math.pi * r_2) \
            + self.M
        y = self.S \
            * math.sqrt(-2 * math.log(r_1)) \
            * math.sin(2 * math.pi * r_2) \
            + self.M
        return [math.floor(x), math.floor(y)]
    except Exception as e:
        raise
if __name__ == '__main__':
    try:
        obj = RndnumBoxMuller()
        obj.generate_rndnum()
        obj.display()
    except Exception as e:
        traceback.print_exc()
        sys.exit(1)
#####Problem 2#####

```

**Output:**



```

0: 1 | 1: 6 | 2: 35 | 3: 124 | * 4: 304 | *** 5: 675 | ***** 6:1235 |
***** 7:1860 | ***** 8:2657 |
***** 9:3162 | *****
10:3122 | ***** 11:2646 |
***** 12:1914 | ***** 13:1169 |
***** 14: 642 | ***** 15: 288 | ** 16: 107 | * 17: 39 | 18: 10 |
19: 3 | 20: 1 |

```

In the first row of the graph we can see, respectively, the histograms of  $u_1$  and  $u_2$  before the transformation and in the second row we can see the values after the transformation, respectively  $z_1$  and  $z_2$ . We can observe that the values before the transformation are distributed uniformly while the histograms of the values after the transformation have the typical Gaussian shape.

### Problem 3:

To find an explicit formula for  $F^{-1}(r)$  for the c.d.f. of a r.v. or to generate  $F(x) = P(X \leq x)$  is not always possible. Even if we can, that may not be the most efficient method for generating a r.v. distributed according to  $F$ . Let us assume the continuous case and that  $X$  has c.d.f.  $F$  and p.d.f.  $f$ . I'll give the discrete case later, which is very similar. The basic idea is to find an alternative probability distribution  $G$ , with density  $g(x)$ , from which we can easily simulate (e.g., inverse-transform etc.). However, we'll also want  $g(x)$  'close' to  $f(x)$ . • So we assume that  $f(x)/g(x)$  is bounded by a constant  $c > 0$ . Hence  $\sup_x \{f(x)/g(x)\} \leq c$ . In practice we want  $c$  close to 1 as possible. So Accept-Reject Algorithm can be shown as below:

1. Generate a r.v.  $Y$  according to  $G$  (remember we assumed this was easy).
2. Generate  $R \sim U(0, 1)$  independent of  $Y$ .
3. If  $U \leq f(Y)/cg(Y)$ , then set  $X = Y$ , i.e., 'accept'; otherwise start again i.e., 'reject'.

The Laplace distribution is similar to the Gaussian/normal distribution, but is sharper at the peak and has fatter tails. It represents the difference between two independent, identically distributed exponential random variables. So we use `numpy.random.laplace` to draw out the random variables.

Python Code:

```

#####Problem 3#####

import numpy as np
from scipy.stats import binom
import seaborn as sns
def rlaplace(n, mu, sigma):
    U = np.random.uniform(0,1,n)

```

```

sign = binom.rvs(1, 0.5, size = n)
sign[sign>0.5] = 1
sign[sign<0.5] = -1
y = mu + sign*sigma/np.sqrt(2)*np.log(1-U)
print(y)
sns.distplot(y)

```

#####Problem 3#####

```
rlaplace(1000,0.5,0.8)
```

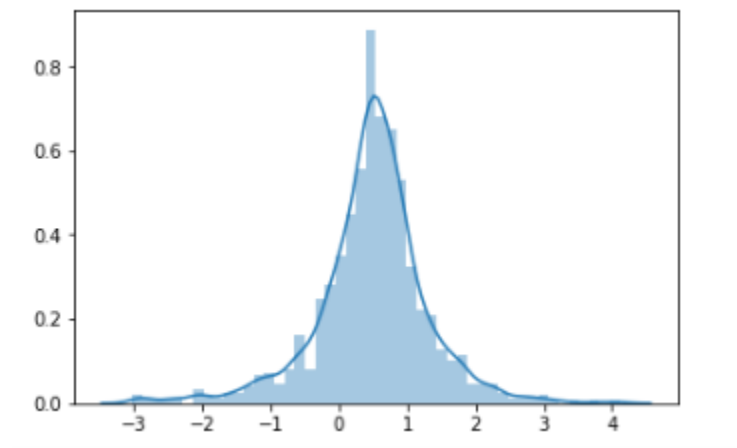
#####Problem 3#####

### Output:

```

[ 1.97957488e+00 9.11064488e-01 -7.47118832e-02 -1.11035006e-01
 1.75052280e-01 1.28033891e+00 3.54853738e-01 1.25000945e+00 7.33231156e-01
 7.30976973e-01 9.66269390e-02 1.11508146e+00 1.62765440e-01 3.78388291e-01
 4.65458059e-02 -8.69660965e-01 4.31252719e-01 1.21465695e+00 4.81954685e-
 01 8.04330333e-01 1.84063739e+00 9.09176418e-01 -8.48805240e-02
 6.81097944e-02 4.97880519e-01 6.07943130e-01 9.75030687e-01 7.98664702e-02
 2.11572906e+00 -3.02104963e-01 5.68779354e-01 6.61962489e-01 8.58086541e-
 01 -2.37536623e-02 3.98677561e-01 4.08136371e-01 -2.01465910e-01
 3.20109031e-01 -1.27358877e+00 4.86182050e-01 6.79726582e-01 -
 2.04511567e+00 -2.59261110e-01 9.84961303e-01 4.62006691e-01 3.45308444e-
 01 7.86371303e-01 9.02604451e-01 1.19131000e-01 6.07052726e-01
 4.47364199e-01 1.31275986e+00 5.03099869e-01 -2.05769767e-01
 1.00345963e+00 -7.50119451e-01 9.90887682e-01 -2.10246610e+00 6.96781387e-
 02 4.74202582e-01 2.95653769e-01 4.75301314e-01 9.93965187e-02 -
 1.24026995e+00.....]

```



#### Problem 4:

##### Python Code:

```
#####Problem 4#####

import numpy as np
import math
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

warnings.filterwarnings('ignore')

n = 1000

u = np.random.uniform(low = 0.0, high = 1.0, size = n)

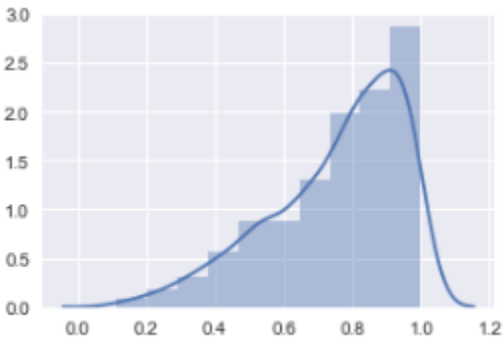
x = u**(1/3)

sns.distplot(x, hist = True, kde=True, bins = 10)

plt.show()

#####Problem 4#####
```

##### Output:



#### Problem 5:

##### Python Code:

```
#####Problem 5#####

import pandas as pd
from scipy.stats import beta
from scipy.stats.mstats import mquantiles

n = 1000

k = 0

j = 0

y = np.zeros(n)

while k < n-1:

    u = np.random.uniform(size = 1)
```



```

j = j+1
x = np.random.uniform(size = 1)
if x*(1-x) > u:
    k = k+1
    y[k] = x
p = np.linspace(start = 0.1, stop = 0.9, num=10)
q_hat = scipy.stats.mstats.mquantiles(y, p)
##q_hat = np.quantile(y,p)
r = beta.ppf(p, 3, 2)
z = np.sqrt(p*(1-p)/(n*beta.pdf(r, 3, 2)**2))
print(q_hat)
print(r)
print(z)
temp = np.array([q_hat, r])
for i in temp:
    sns.distplot(i, hist = True, kde = True, color = 'darkblue')

plt.show()

```

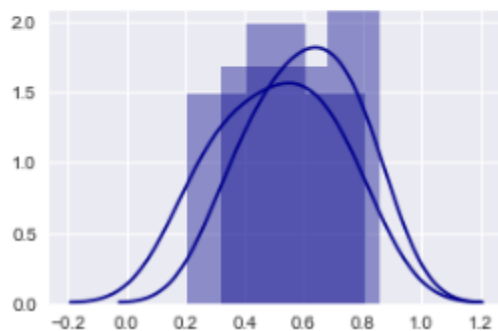
#####Problem 5#####

### Output:

```

[0.20360727 0.28521864 0.34565156 0.41911701 0.4965357 0.54697297
 0.60732269 0.66017803 0.72476103 0.80970146]
[0.32046058 0.40829619 0.47627164 0.53494954 0.58857456 0.63953933
 0.68961098 0.7405407 0.7947675 0.85744068]
[0.00113286 0.0010457 0.00099354 0.00095421 0.00092081 0.00089017
 0.00086031 0.00082954 0.00079568 0.00075429]

```



## Problem 6:

### Python Code:

```
#####Problem 6#####

import numpy as np
import math
import scipy.stats
import seaborn as sns
import collections as col

n = 1000
theta = 0.5
u = np.random.uniform(size = n)
v = np.random.uniform(size = n)
x = (1+np.log(v)/np.log(1-(1-theta)**u))
x = np.floor(x)

k = []
for i in range(1, int(max(x))+1):
    k.append(i)

p = []
for j in range(0, len(k)):
    temp = -1/np.log(1-theta)*(theta*k[j])/k[j]
    p.append(temp)

se = []
for i in range(0, len(p)):
    temp = np.sqrt(p[i]*(1-p[i])/n)
    se.append(temp)

c = col.Counter(x).values()
c = list(c)
p_hat = []
for i in range(0, len(c)):
    temp = c[i]/n
    p_hat.append(temp)
```

```

print("P_hat: ", p_hat)
print("\nP: ", p)
print("\nse: ", se)
sns.distplot(x, hist = True, kde = True, bins = 8)
#####Problem 6#####

```

### Output:

```

P_hat:  [0.702, 0.188, 0.01, 0.068, 0.026, 0.003, 0.002, 0.001]

P:  [0.7213475204444817, 0.7213475204444817, 0.7213475204444816,
7213475204444817, 0.7213475204444817]

se:  [0.014177632919252768, 0.014177632919252768, 0.014177632919
1925277, 0.014177632919252768, 0.014177632919252768]

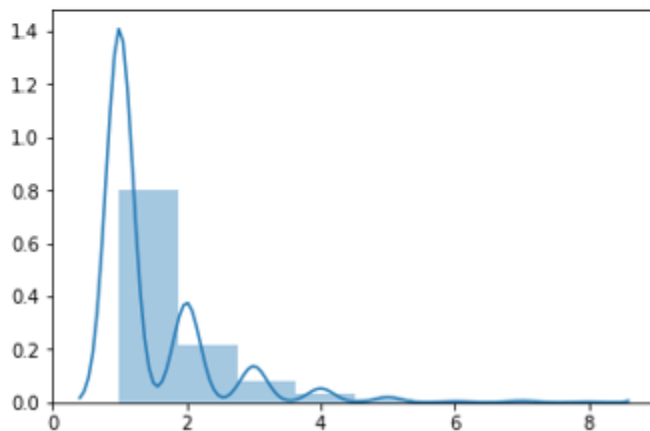
C:\Users\anmol\Anaconda3\lib\site-packages\matplotlib\axes\_axes
s been replaced by the 'density' kwarg.
warnings.warn("The 'normed' kwarg is deprecated, and has been

```

```

.]: <matplotlib.axes._subplots.AxesSubplot at 0x24d0372f6d8>

```



## Problem 7:

### Python Code:

```
#####Problem 7#####

import numpy as np
from scipy.stats import gamma
from matplotlib import pyplot as plt

#-----

# plot the distributions
k_values = [1, 2, 3, 4]
theta_values = [1, 1, 2, 2]
linestyles = ['-', '--', ':', '-.']
x = np.linspace(1E-6, 10, 1000)

#-----

# plot the distributions
fig, ax = plt.subplots(figsize=(5, 3.75))

for k, t, ls in zip(k_values, theta_values, linestyles):
    dist = gamma(k, 0, t)
    plt.plot(x, dist.pdf(x), ls=ls, c='black',
             label=r'$k=% .1f, \theta=% .1f$' % (k, t))

plt.xlim(0, 10)
plt.ylim(0, 0.45)

plt.xlabel('$x$')
plt.ylabel(r'$p(x|k, \theta)$')
plt.title('Gamma Distribution')

plt.legend(loc=0)
plt.show()

###from scipy.stats import gamma
import numpy as np
import matplotlib.pyplot as plt

x = np.arange(0,10,.1)
```

```

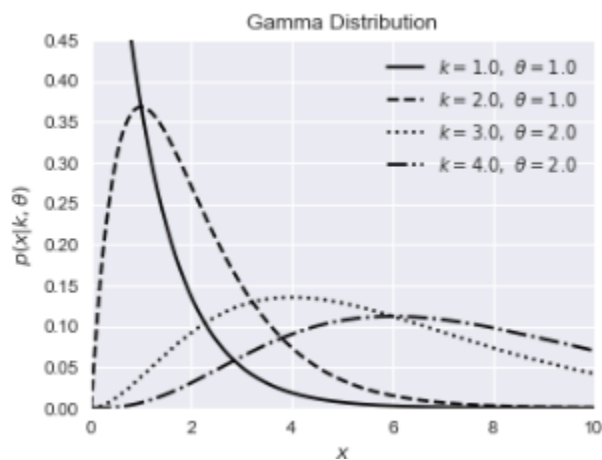
y1 = np.random.gamma(shape=4, scale=3, size=1000) + 2 # sets loc = 2
y2 = np.hstack((y1, 10*np.random.rand(100))) # add noise from 0 to 10

# fit the distributions, get the PDF distribution using the parameters
shape1, loc1, scale1 = gamma.fit(y1)
g1 = gamma.pdf(x=x, a=shape1, loc=loc1, scale=scale1)
g1
hist(g1)
import seaborn as sns
sns.distplot(g1)

#####Problem 7#####

```

### Output:



<matplotlib.axes.\_subplots.AxesSubplot at 0x24d03815438>

