

gibbs

November 3, 2018

Question 1 Algorithm:

We have used a Gibbs sampler to estimate the marginal distribution generated from the conditional distributions:

$$p(x|y) \propto ye^{-yx}, 0 < x < B < \infty$$

$$p(y|x) \propto xe^{-yx}, 0 < y < B < \infty, \text{ where } B \text{ is a known positive constant.}$$

First, we have used initial values of x and y to be random numbers generated from Uniform[0, B]. Then, we have created a $T \times 3$ matrix called *chain* filled with zeros, where T = number of iterations.

Since the marginal conditional density function of $x|y$, $p(x|y) \propto ye^{-yx}$ and the range of x is from 0 to B , the cumulative density function of $x|y$, $F(x|y) = \int_0^x ye^{-yx} dx$.

Note that the conditional density function of $x|y$ follows the exponential distribution. Then, $F(x|y) = \int_0^x ye^{-yx} dx = 1 - e^{-yx}$.

Since the ranges of both x and y are from 0 to B , and it is not to infinity, the cumulative functions of both x and y are less than 1. Therefore, we need to rescale this by dividing $\int_0^B xe^{-yx} dx$ and $\int_0^B xe^{-yx} dy$ respectively. For Inverse Transform Sampling, we have first generated u from Uniform[0, 1] and let $u = \frac{\int_0^x xe^{-yx} dx}{\int_0^B xe^{-yx} dx} = \frac{1-e^{-yB}}{1-e^{-yx}}$. Solving for x , we have $x = -\frac{1}{y} \ln(1 - u(1 - e^{-yB}))$.

Similarly, we have generated v from Uniform[0, 1] and used Inverse Transform Sampling. Let $v = \frac{\int_0^y xe^{-yx} dy}{\int_0^B xe^{-yx} dy} = \frac{1-e^{-xB}}{1-e^{-xy}}$. Solving for y , we have $y = -\frac{1}{x} \ln(1 - v(1 - e^{-xB}))$.

The first column of *chain* will represent the iteration number. From each iteration of the sampler, we have stored value of x into the second column of *chain* and value of y into the third column of *chain*.

Finally, this function returns the matrix *chain* with stored x and y values.

Please note that we have not included thinning process in this function.

The algorithm is as follows:

```
In [1]: %matplotlib inline
import random, math
from math import *
from random import *
import numpy as np
from numpy import *
import matplotlib.pyplot as plt
from matplotlib.pyplot import *

def gibbs(B, T):
```

```

x = float(np.random.uniform(0, B, 1))
y = float(np.random.uniform(0, B, 1))
chain = np.zeros((T, 3))
chain[:, 0] = range(1, T + 1)
for i in range(T):
    u = float(np.random.uniform(0, 1, 1))
    v = float(np.random.uniform(0, 1, 1))
    x = -np.log(1 - u * (1 - np.exp(-y * B))) / y
    y = -np.log(1 - v * (1 - np.exp(-x * B))) / x
    chain[i, 1] = x
    chain[i, 2] = y
return(chain)

```

Question 2 Histograms of values for x , for $B = 5$ and for sample sizes $T = 500, 5000, 50000$ are as follows:

```

In [2]: G1 = gibbs(B = 5, T = 500)
        G2 = gibbs(B = 5, T = 5000)
        G3 = gibbs(B = 5, T = 50000)

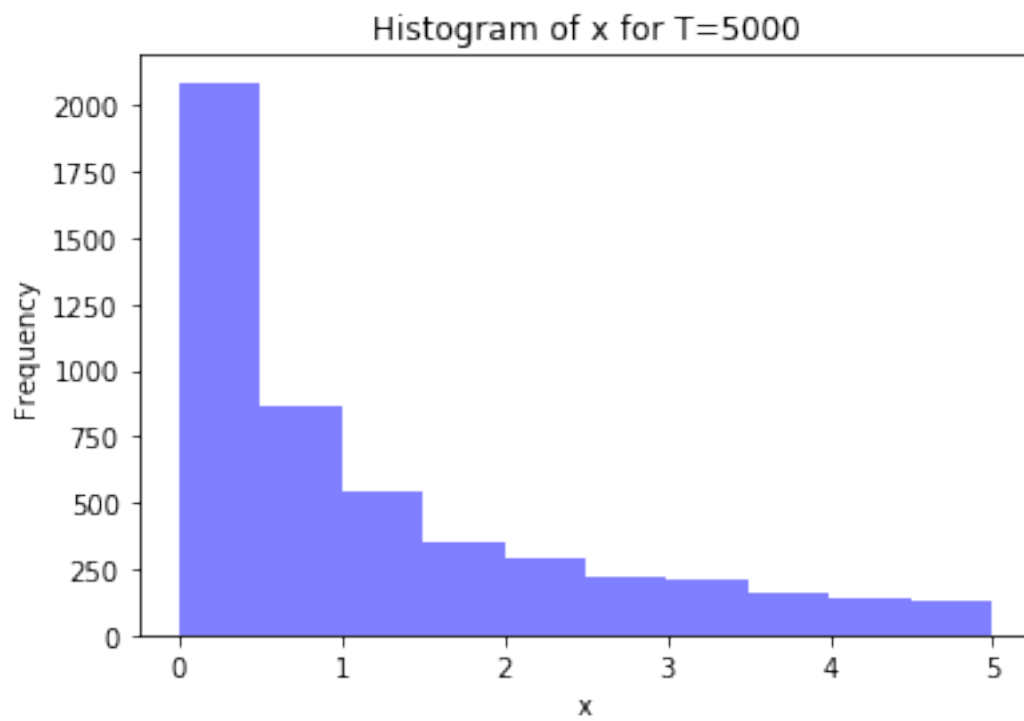
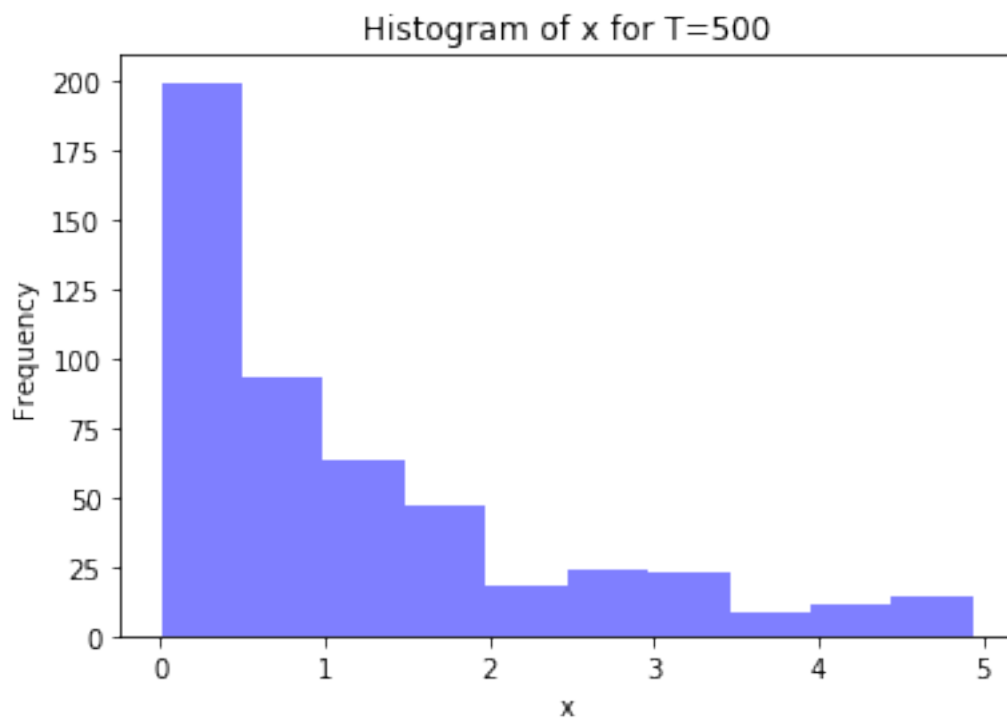
xx = G1[:,1]
x2 = G2[:,1]
x3 = G3[:,1]

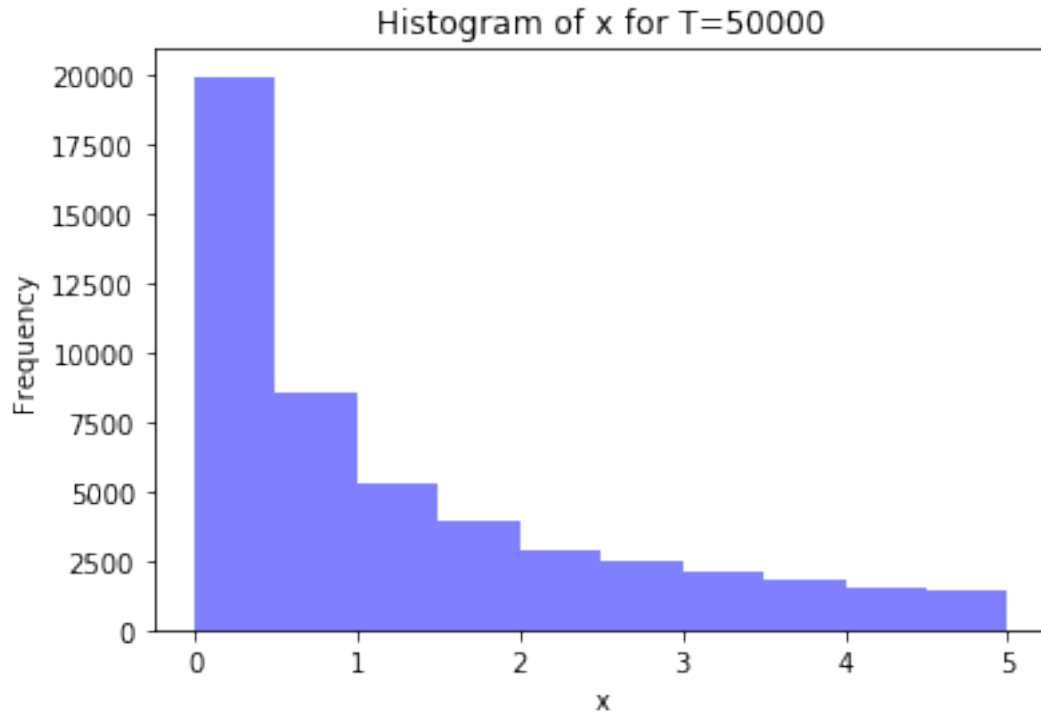
n,bins,patches = plt.hist(xx, facecolor='blue', alpha=0.5)
plt.xlabel('x')
plt.ylabel('Frequency')
plt.title(r'Histogram of x for T=500')
plt.show()

n,bins,patches = plt.hist(x2, facecolor='blue', alpha=0.5)
plt.xlabel('x')
plt.ylabel('Frequency')
plt.title(r'Histogram of x for T=5000')
plt.show()

n,bins,patches = plt.hist(x3, facecolor='blue', alpha=0.5)
plt.xlabel('x')
plt.ylabel('Frequency')
plt.title(r'Histogram of x for T=50000')
plt.show()

```





Note that the histograms of x follows exponential distribution. As we increase the number of iteration (T), we get thinner tails.

Question 3 An estimate of the expectation of X , $\mathbb{E}_{p(X)}[X]$, by using the 500, 5000, and 50000 samples from the sampler is as follows:

```
In [4]: print("Estimate of the expectation for T = 500:", round(mean(xx), 4))
        print("Estimate of the expectation for T = 5000:", round(mean(x2), 4))
        print("Estimate of the expectation for T = 50000:", round(mean(x3), 4))
```

```
Estimate of the expectation for T = 500: 1.1659
Estimate of the expectation for T = 5000: 1.2091
Estimate of the expectation for T = 50000: 1.2772
```