

# Exercise No. 10

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## 2 - Probability distribution functions

We have given a probability distribution function  $p(x)$  in the domain  $[0, a)$  by

$$p(x) = bx \tag{1}$$

Where  $b$  is the normalization factor. At first we need to calculate  $b$  as a function of  $a$  to normalize the given pdf. Therefore we integrate the pdf from 0 to  $a$  which has to be one.

$$\int_0^a bx \, dx \stackrel{!}{=} 1$$

For the solution we obtain

$$b = \frac{2}{a^2}$$

Our normalized pdf is now

$$p(x) = \frac{2}{a^2}x$$

For the calculation we used a random set of numbers which are uniformly distributed between 0 and 1. With the rejection method we calculated random numbers which obeyed equation 2.1 for  $a = 0.5$ . So we generated another set of random numbers uniformly distributed as before to check if

$$v \leq \frac{p(x)}{g(x)}$$

with

$$g(x) = \frac{2}{a}$$

because  $p(x)$  reaches its maximum at  $x = a$

```

1 import numpy as np
2 import numpy.random as np.random
3 import matplotlib.pyplot as plt
4
5 #maximal point for plotting intervall as given in the sheet
6 a = 0.5
7
8 #define linspace for the given intervall
9 x = np.linspace(0.001, a, 100)
10 #define function with normalization factor, therefore b = 2 / a^2
11 f = lambda x: (2 / a**2) * x
12 fx = f(x)
13
14 M = 2 / a #scale factor for rejection sampling g(x)
15 u1 = np.random.rand(10000) * a #uniform random samples scaled out in [0, 1)
16 u2 = np.random.rand(10000) #uniform random samples in [0, 1)
17 idx = np.where(u2 <= f(u1) / M)[0] #rejection criterion
18 v = u1[idx]
19
20 #plot histogram
21 fig, ax = plt.subplots()
22 ax.hist(v, normed = 1, bins = 40, alpha = 0.7)
23 ax.plot(x, fx, 'r')
24 ax.set_title('estimated_efficiency = %3.1f%%'%(100 * len(v) / len(u1)))
25 plt.savefig('pdf.png')
26
27 #plot accepted and rejected areas
28 fig, ax = plt.subplots()
29 ax.plot(u1, u2, '.', c = 'r', label = 'rejected', alpha = 0.2)
30 ax.plot(u1[idx], u2[idx], '.', c = 'g', label = 'accepted', alpha = 0.4)
31 ax.legend(fontsize = 14)
32 plt.savefig('accepted_rejected.png')
33
34 plt.show()

```

Here are the plots for the solutions given with the code above. In figure 1 is show the histogram with the random number sample and the overplotting probability distribution function. In figure 2 is shown the individual random numbers which were accepted or rejected by the given algorithm. Also for this graph it was chosen a sampling of 10000 which gave us a reasonable fit (by eye) as you can see.

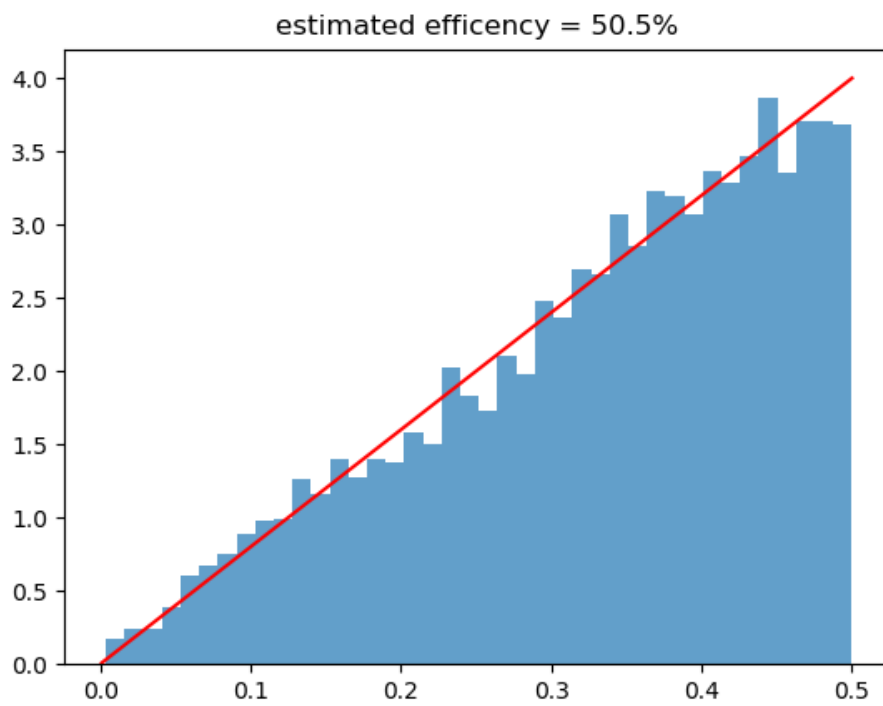


Figure 1: histogram for the pdf with overplotting equation 2.1

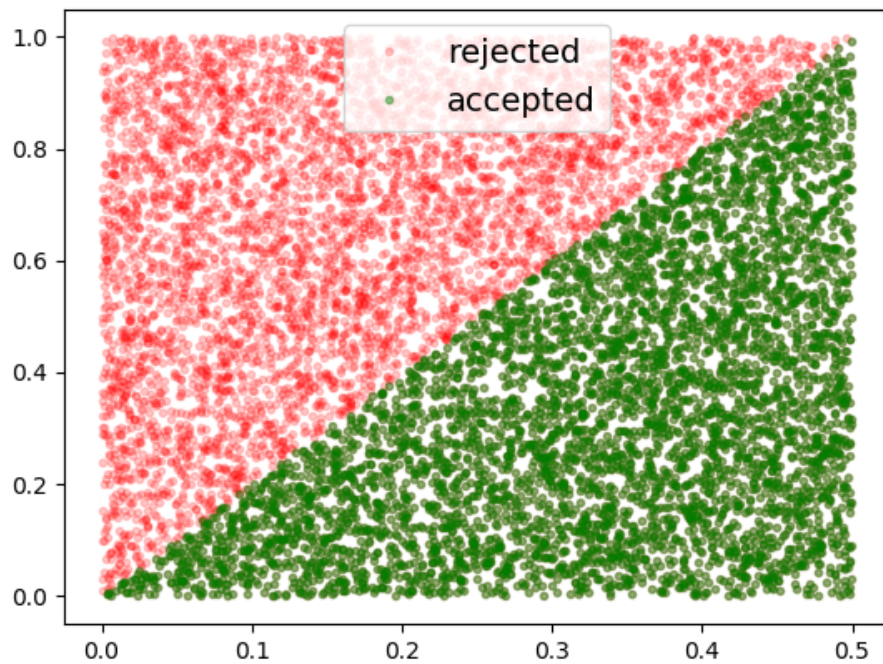


Figure 2: accepted and rejected random numbers

### 3 - Determine $\pi$ with random numbers

To compute the number  $\pi$  we use the function

$$f(x) = \sqrt{1 - x^2} \quad \text{for } 0 \leq x \leq 1 \quad (2)$$

Also we using the rejection method as above with a slightly adjustment for the further calculation of the accuracy of the result as a function of the random number. Furthermore, due to symmetry we only need to sample from the upper right corner of the box (one quarter of the circle). In this case the fomula to determine  $\pi$  can be explicitly written as:

$$\frac{pointsInCircle}{totalPoints} = \frac{\pi \cdot L^2}{4 \cdot L^2}$$

So  $\pi$  can be approximated with

$$\pi = \frac{pointsInCircle}{totalPoints} \cdot 4$$

Like above you can see in figure 3 histogram of the random number sample which follows the given function. Figure 4 show the accepted and rejected values. Also we have an approximation of  $\pi$  for this sample of  $\pi_{approximation} = 3.14404$ . This calculation was made with a random number sample of 100000.

The graph for the error calculation is shown in figure 5. You can see that the accuracy of the result will be better with higher random number sample.

```

1 import numpy as np
2 import numpy.random as np.random
3 import matplotlib.pyplot as plt
4
5 #define linspace for the given interval
6 x = np.linspace(0.001, 1, 100)
7 #define function for pi calculation
8 f = lambda x: np.sqrt(1 - x**2)
9 fx = f(x)
10
11 #define fuction for rejection sampling
12 def approx(number_sample):
13     M = 1 #scaling factor can be one for this
14     function
15     u1 = np.random.rand(number_sample) #uniform random samples in [0, 1)
16     u2 = np.random.rand(number_sample) #uniform random samples in [0, 1)
17     idx = np.where(u2 <= f(u1) / M)[0] #rejection criterion
18     v = u1[idx]
19
20     #approximation of pi
21     #due to symmetry we only need to sample from the upper right corner of the
22     box
23     one quarter of the circle). In this case the formula to determine pi can be
24     explicitly written as: pointsInCircle / totalPoints = pi * L^2 / (4 * L^2)
25     approximation = len(v) / number_sample * 4
26
27     return [v, idx, u1, u2, approximation]
28
29 w = approx(100000)
30 #plot histogram
31 fig, ax = plt.subplots()
32 ax.hist(w[0], normed = 1, bins = 40, alpha = 0.7)
33 ax.plot(x, fx, 'r')
34 ax.set_title('estimated_efficiency = %3.1f%%' % (100 * len(w[0]) / len(w[2])) +
35             '\napproximation_of_pi = ' + str(w[4]))
36 plt.savefig('pi.png')
37
38 #plot accepted and rejected areas
39 fig, ax = plt.subplots()
40 ax.plot(w[2], w[3], '.', c = 'r', label = 'rejected', alpha = 0.2)
41 ax.plot(w[2][w[1]], w[3][w[1]], '.', c = 'g', label = 'accepted', alpha = 0.4)
42 ax.legend(fontsize = 14)
43 plt.savefig('accepted-rejected-pi.png')
44
45 #error calculation of the approximated pi to the pi of numpy
46 #in dependence of the magnitude of random numbers
47 sample_numbers = np.logspace(1, 6, num = 100)
48 pi_approximations = [approx(int(i))[4] for i in sample_numbers]
49 error = [(np.abs(i - np.pi) / np.pi) for i in pi_approximations]
50 fig, ax = plt.subplots()
51 ax.semilogx(sample_numbers, error)
52 ax.set_xlabel('magnitude_random_number')
53 ax.set_ylabel('error')
54 plt.savefig('error-calculation-pi.png')
55 plt.show()

```

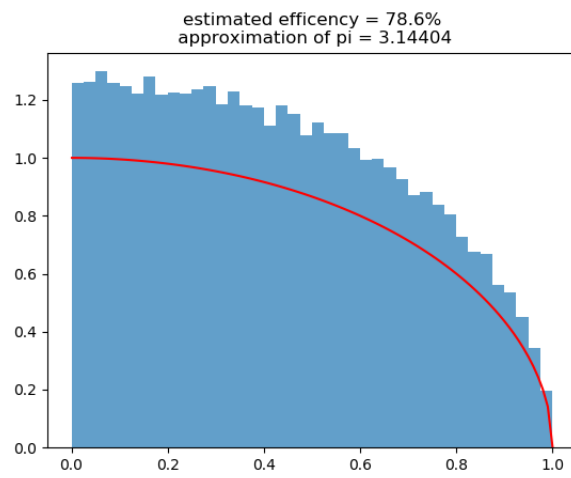


Figure 3: histogram for the function 2

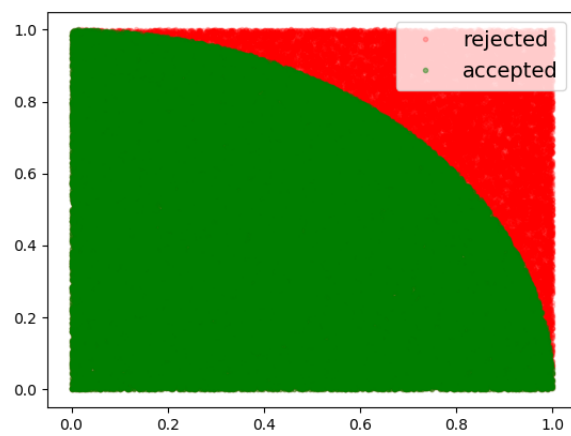


Figure 4: accepted and rejected random numbers

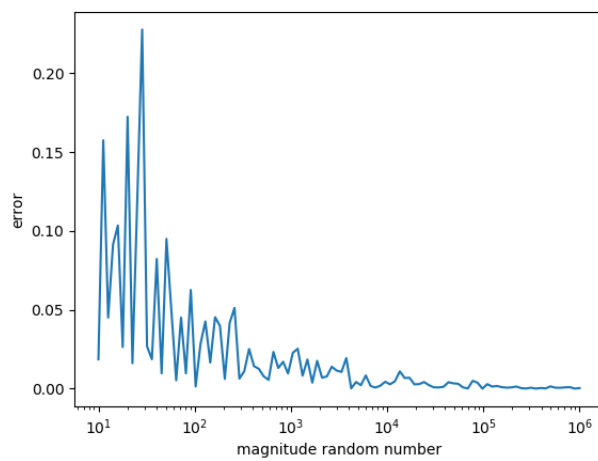


Figure 5: accuracy of the result as function of the number of samples