# 08ex\_MonteCarlo

#### March 14, 2020

## 1. Radioactive decay chain

 $Tl^{208}$  decays to  $Pb^{208}$  with a half-lieve of 3.052 minutes. Suppose to start with a sample of 1000 Thallium atoms and 0 of Lead atoms.

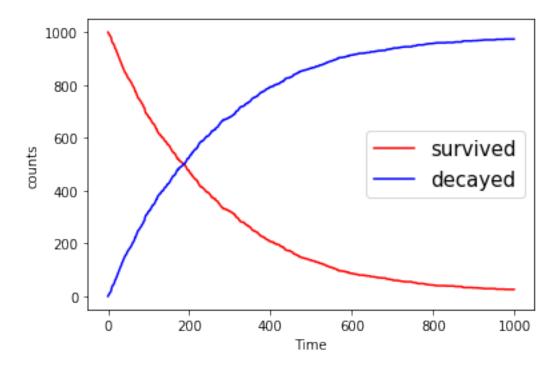
- Take steps in time of 1 second and at each time-step decide whether each Tl atom has decayed or not, accordingly to the probability  $p(t) = 1 2^{-t/\tau}$ . Subtract the total number of Tl atoms that decayed at each step from the Tl sample and add them to the Lead one. Plot the evolution of the two sets as a function of time
- Repeat the exercise by means of the inverse transform method: draw 1000 random numbers from the non-uniform probability distribution  $p(t) = 2^{-t/\tau} \frac{\ln 2}{\tau}$  to represent the times of decay of the 1000 Tl atoms. Make a plot showing the number of atoms that have not decayed as a function of time

```
In [1]: import matplotlib.pyplot as plt
        %matplotlib inline
        import math
        import numpy as np
        def pt (t):
            return 1-2**(-t/(3.052*60))
        def pdf_expo(t):
            return 2**(-t/(3.052*60)*math.log(2)/(3.052*60))
        time=np.arange(0,1000)
        probs=np.random.uniform(0,1,1000)
        Ti=np.array([1000])
        Pb=np.array([0])
        for t in time[1:]:
            decay=0
            for i in range(len(probs)):
                if(i>=len(probs)):
                    break
                if(probs[i]<(pt(t))):</pre>
                    probs=np.delete(probs,[i])
                    i-=1
                    decay+=1
            Pb=np.append(Pb, Pb[-1]+decay)
```

## Ti=np.append(Ti, Ti[-1]-decay)

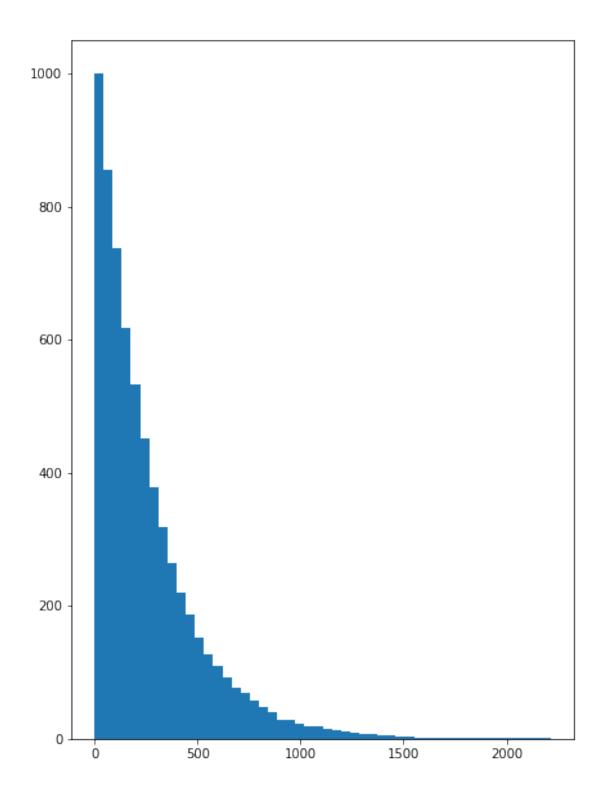
```
plt.plot(time, Ti, c="red", label="survived")
plt.plot(time, Pb, c="blue", label="decayed")
plt.xlabel("Time")
plt.ylabel("counts")
plt.legend(fontsize=15,loc="best")
plt.show
```

Out[1]: <function matplotlib.pyplot.show(\*args, \*\*kw)>



```
In [2]: def exp_pdf(p):
            return -np.log(1-p)/(np.log(2)/(3.056*60))
        x = np.random.uniform(0,1,1000)
        fig, ax = plt.subplots(1,1, figsize=(7, 10))
        t=exp_pdf(x)
        ax.hist(t,bins=50,cumulative=-1)
                                       618., 533., 451.,
Out[2]: (array([1000.,
                        855.,
                                738.,
                                                             378.,
                                                                     319.,
                                                                            264.,
                        187.,
                               153., 127.,
                                              109.,
                                                       92.,
                                                              77.,
                 220.,
                                                                      70.,
                                                                             57.,
                  48.,
                          41.,
                                 28.,
                                        28.,
                                                22.,
                                                       19.,
                                                              18.,
                                                                      15.,
                                                                             14.,
                           9.,
                                  8.,
                                                                       3.,
                  12.,
                                         8.,
                                                 5.,
                                                        5.,
                                                               4.,
                                                                              2.,
                   2.,
                           2.,
                                  2.,
                                         2.,
                                                 2.,
                                                        1.,
                                                               1.,
                                                                       1.,
                                                                              1.,
```

```
1.]),
                 1., 1.,
                              1.,
array([2.26915456e-01, 4.45337057e+01, 8.88404960e+01, 1.33147286e+02,
       1.77454077e+02, 2.21760867e+02, 2.66067657e+02, 3.10374447e+02,
       3.54681238e+02, 3.98988028e+02, 4.43294818e+02, 4.87601609e+02,
       5.31908399e+02, 5.76215189e+02, 6.20521979e+02, 6.64828770e+02,
       7.09135560e+02, 7.53442350e+02, 7.97749140e+02, 8.42055931e+02,
       8.86362721e+02, 9.30669511e+02, 9.74976302e+02, 1.01928309e+03,
       1.06358988e+03, 1.10789667e+03, 1.15220346e+03, 1.19651025e+03,
       1.24081704e+03, 1.28512383e+03, 1.32943062e+03, 1.37373741e+03,
       1.41804420e+03, 1.46235099e+03, 1.50665778e+03, 1.55096458e+03,
       1.59527137e+03, 1.63957816e+03, 1.68388495e+03, 1.72819174e+03,
       1.77249853e+03, 1.81680532e+03, 1.86111211e+03, 1.90541890e+03,
       1.94972569e+03, 1.99403248e+03, 2.03833927e+03, 2.08264606e+03,
       2.12695285e+03, 2.17125964e+03, 2.21556643e+03]),
<a list of 50 Patch objects>)
```



## 2. Rutherford Scattering

The scattering angle  $\theta$  of  $\alpha$  particles hitting a positively charged nucleus of a Gold atom (Z=79) follows the rule:

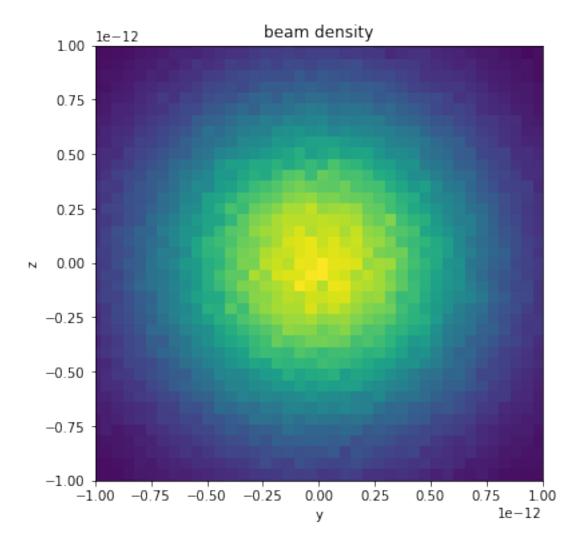
$$\tan\frac{1}{2}\theta = \frac{Ze^2}{2\pi\epsilon_0 Eb}$$

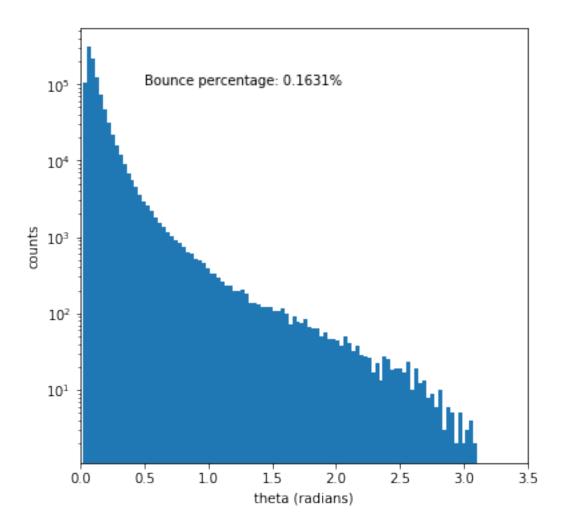
where E = 7.7 MeV and b beam is the impact parameter. The beam is represented by a 2D gaussian distribution with  $\sigma = a_0/100$  for both coordinates ( $a_0$  being the Bohr radius). Assume 1 million  $\alpha$  particles are shot on the gold atom.

Computing the fraction of particles that "bounce back",i.e. those particle whose scattering angle is greater than  $\pi/2$  (which set a condition on the impact parameter b)

```
In [3]: import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        import math
        Z = 79
        e=1.602176565*10**(-19)
        E=7.7*10**(6)*e
        a0=5.2917721067*10**(-11)
        e0=8.8541878176*10**(-12)
        constants=Z*e**2/(2*np.pi*e0*E)
        n=10**6
        y = np.random.normal(0, a0/100, n)
        z = np.random.normal(0, a0/100, n)
        b=np.array([math.sqrt(yb**2+zb**2) for yb,zb in zip(y,z)])
        plt.figure(figsize=(6,6))
        plt.hist2d(y, z,bins=100)
        plt.xlabel('y')
        plt.ylabel('z')
        plt.xlim(-10**(-12),10**(-12))
        plt.ylim(-10**(-12),10**(-12))
        plt.title("beam density")
        plt.show()
        theta=2*np.arctan(constants/b)
        n_bounce=np.sum(theta>np.pi/2)
        plt.figure(figsize=(6,6))
        plt.hist(theta,bins=100)
        plt.xlabel('theta (radians)')
        plt.ylabel('counts')
        plt.xlim(0,3.5)
        plt.yscale('log')
        plt.text(0.5,1e5, "Bounce percentage: "+str(n_bounce/1e4)+"%")
```

plt.show()





# 3. Monte Carlo integration: hit/miss vs mean value method Consider the function

$$f(x) = \sin^2 \frac{1}{x(2-x)}$$

- Compute the integral of f(x) between 0 and 2 with the hit/miss method. Evaluate the error of your estimate
- Repeat the integral with the mean value method. Evaluate the error and compare it with the previous one

```
In [4]: import numpy as np
    import math

def f3 (x):
    return (math.sin(1.0/(x*(2-x))))**2

def hitmiss (a, b, n):
```

```
points = np.random.random((n,2))
            #remap points
            points[:,0]*=(b-a)
            points[:,0]+=a
            #counting
            cont =0
            for p in points:
                if f3(p[0])>p[1]:
                    cont+=1
            area= (b-a)*1*cont/n
            return area
        def av_hitmiss(a,b,n):
            suma=0
            for i in range (30):
                suma +=hitmiss(a,b,n)
            return suma/30
        def mean val (a,b,n):
            #geenrate and map on range
            samples=np.random.random(n)
            samples*=(b-a)
            samples+=a
            s=np.sum([f3(x) for x in samples])
            return s*(b-a)/n
        print(av_hitmiss(0,2, 10000))
        print(av_hitmiss(0,2, 10000))
        print(av_hitmiss(0,2, 10000))
        print(av_hitmiss(0,2, 10000))
        print(mean_val(0,2, 10000))
        print(mean val(0,2, 10000))
        print(mean_val(0,2, 10000))
        print(mean_val(0,2, 10000))
1.4533933333333333
1.4494733333333333
1.451526666666669
1.4497133333333333
1.4540389330931518
1.451755913195554
1.447514478041791
1.458286227134121
```

#numbers between 0 and 1, perfect for the y, to be redefined for x

### 4. Monte Carlo integration in high dimension

• Start of by computing the area of a circle of unit radius, by integrating the function

$$f(x,y) = \begin{cases} 1 & x^2 + y^2 \le 1\\ 0 & \text{elsewhere} \end{cases}$$

• Generalize the result for a 10D sphere

```
In [5]: def dist(p):
            return np.sum(p**2)
        def mc_int(n, dim):
            points=np.random.random((n,dim))
            cont=0
            for p in points:
                if dist(p)<1:</pre>
                    cont+=1
            return (2**dim)*cont/n
        print("\t my value \t etimated value")
        print ("2dim\t",mc_int(10000, 2),"\t", math.pi)
        print ("3dim\t",mc_int(10000, 3),"\t", math.pi*4/3)
        print ("10dim\t",mc_int(10000, 10),"\t", math.pi**5/120) #volume ipersfera 10-dim
        #servono più numeri
        print ("10dim\t",mc_int(100000, 10),"\t", math.pi**5/120, " need more points to converge
                          etimated value
        my value
2dim
             3.1448
                           3.141592653589793
            4.1984
                           4.1887902047863905
3dim
10dim
             1.8432
                             2.550164039877345
10dim
              2.53952
                               2.550164039877345 need more points to converge
In [6]: x=np.arange(1,5,1)
        integ=[mc_int(10**a,2)for a in x]
       print(integ)
[4.0, 3.2, 3.148, 3.1376]
```

# 5. Monte Carlo integration with importance sampling

Calculate the value of the integral:

$$I = \int_0^1 \frac{x^{-1/2}}{e^x + 1} dx$$

using the importance sampling method with  $w(x) = 1/\sqrt{x}$ . You should get a result about 0.84

```
In [7]: import numpy as np
        import math
        def make_grid(xmin, xmax, n):
            return np.random.uniform(xmin,xmax, int(n))
        def integ_mean (f, a,b,N):
            x=f(np.random.uniform(a,b,int(N))*(b-a))
            return (b-a)*np.sum(x)/float(N)
        def wx (x):
            return 1/np.sqrt(x)
        def fx (x):
            return 1.0/(np.sqrt(x)*(np.exp(x)+1))
        N=1e6
        for i in range(6):
            N=10**i
            x=make_grid(0,1,N)
            w_integ=integ_mean(wx,0,1,N)
            tot_integ=np.sum(np.array([fx(xi)/wx(xi) for xi in x]))*w_integ/N
            print("Number of points : 10^", i, "\tintegral value: ",tot_integ)
Number of points : 10<sup>0</sup>
                                   integral value: 0.40097245878388754
Number of points : 10<sup>1</sup>
                                   integral value: 0.49669916760171057
Number of points : 10<sup>2</sup>
                                   integral value: 0.7252949489210867
Number of points : 10<sup>3</sup>
                                   integral value: 0.7300425920940372
Number of points : 10<sup>4</sup>
                                   integral value: 0.7620327195553975
Number of points : 10<sup>5</sup>
                                   integral value: 0.7642623134731534
```

## In []: