Sheet 1

```
In [1]: # imports
import random
import math
import matplotlib.pyplot as plt
```

Exercise 1: Random number generators

(a) Generate 100000 uniformly distributed random numbers between 0 and 1 and save the output.

```
In [2]: xs = [random.random() for _ in range(100000)]
```

(b) Write a program which calculates the average value, the variance and the error of the mean of given data and use it to evaluate the random numbers generated in (a)

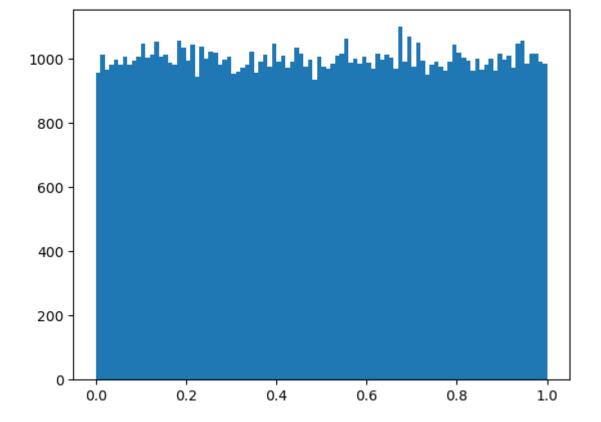
```
In [4]: x_mean = mean(xs)
x_var, x_err = var(xs)
x_mean, x_var, x_err
```

Out[4]: (0.5000713557629796, 8337.363174492417, 0.2887449250548383)

(c) Uniformity Test: Create a histogram of the data with 100 bins and plot it.

```
In [5]: plt.hist(xs, bins=100)
plt.plot()
```

Out[5]: []

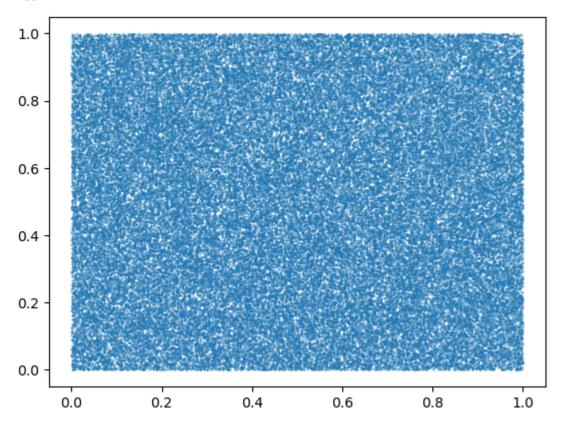


(d) Screen Pixel Test

```
In [6]: xs = [random.random() for _ in range(100000)]
ys = [random.random() for _ in range(100000)]

plt.scatter(xs, ys, 0.1)
plt.plot()
```

```
Out[6]: []
```



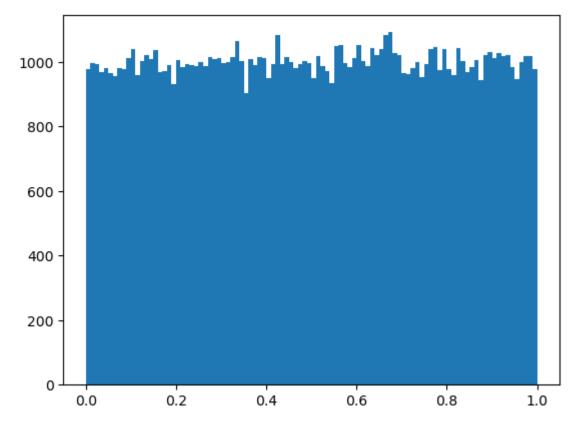
(e) Program your own linear congruential random number generator

```
In [25]: class MyPRNG:
    def __init__(self, seed = 0):
        self.seed = seed
        self.x_ = seed

def random(self):
        a = 1664525
        b = 1013904223
        m = 2**32
        x = ((a * self.x_ + b) % m)
        self.x_ = x
        return x / 2**32
```

```
In [26]: prng = MyPRNG()
    xs = [prng.random() for i in range(100000)]
    plt.hist(xs, bins=100)
    plt.plot()
```

Out[26]: []



Exercise 2: Your first Monte Carlo Simulation

```
In [33]: n = 1000000

hit = 0
for i in range(n):
    x, y = random.random(), random.random()
    hit += 1 if (x*x + y*y < 1) else 0
pi = 4 * hit / n
pi</pre>
```

Out[33]: 3.141644

Exercise 3: Metropolis Criterion

(a)

The Metropolis Criterion states $w_{ij}=min(1,\frac{P_j}{P_i})$. With the Boltzmann Distribution P_i this results in $w_{ij}=min(1,e^{-\beta\Delta E})$.

 $\Delta E_{ij} < 0$ results in $w_{ij} = min(1,e^{-eta\Delta E}) = e^{-eta\Delta E}$. Additionally $\Delta E_{ij} = -\Delta E_{ji}$ leads to $w_{ji} = min(1,e^{-eta\Delta E_{ji}}) = 1$ and thus:

$$\frac{\omega_{ij}}{\omega_{ji}} = \frac{e^{-\beta \Delta E_{ij}}}{1} = e^{-\beta \Delta E_{ij}} \tag{1}$$

resulting in *detailed balance*.

 $\Delta E>0$ results in $w_{ij}=min(1,e^{-eta\Delta E_{ij}})=1$ and $w_{ji}=min(1,e^{-eta\Delta E_{ji}})=e^{-eta\Delta E_{ji}}$ thus:

$$rac{\omega_{ij}}{\omega_{ji}} = rac{1}{e^{-eta \Delta E_{ji}}} = e^{-eta \Delta E_{ij}}$$
 (2)

resulting in *detailed balance*.

(b)

With
$$\Delta E_{ij} = -\Delta E_{ji}$$
 and
$$\omega_{ij} = \frac{e^{-\beta \Delta E_{ij}}}{e^{-\beta \Delta E_{ij}} + 1} = \frac{1}{e^{\beta \Delta E_{ij}} + 1} \text{ then:}$$

$$\frac{\omega_{ij}}{\omega_{ji}} = \frac{e^{-\beta \Delta E_{ij}} + 1}{e^{\beta \Delta E_{ij}} + 1} = e^{-\beta \Delta E_{ij}}$$

(c)

Let the energy difference with be the pair potential $\Delta E_{ij} = V_{ij} = V(\mathbf{r}_i, \mathbf{r}_j)$.

For the Metropolis Criterion we then get:

$$w_{ij} = min(1, e^{-eta \Delta E}) = min(1, e^{-eta V_{ij}}) = \left\{egin{array}{cc} 1, & \|\mathbf{r}_{ij}\| \geq \sigma \ 0, & \|\mathbf{r}_{ij}\| < \sigma \end{array}
ight.$$

Heat bath:

$$w_{ij} = min(1, e^{-eta \Delta E}) = rac{e^{-eta V_{ij}}}{e^{-eta V_{ij}} + 1} = \left\{egin{array}{cc} 0.5, & \|\mathbf{r}_{ij}\| \geq \sigma \ 0, & \|\mathbf{r}_{ij}\| < \sigma \end{array}
ight.$$

Exercise 4: Ising model

(a) At low temperatures stable areas form. With the increase of temperature these areas diffuse into noise. This phase transition occurs at approximately T=2.5. For the phase transition the Wolff Algorithm seems appropriate due to critical slowing down while Metropolis is better outside of this "transition zone".

- 1. select random cell \boldsymbol{c}
- 2. calculate energy $E_i = H_i = -J \sum_{j,k \in \mathcal{N}} s_j s_k$
- 3. flip spin of cell c and calculate E_{j}
- 4. calculate energy difference $\Delta E = H_i H_j$
- 5. accept flip with $w_i j = min(1, e^{-eta \Delta E})$ otherwise reject and flip to original spin
- 6. goto 1.