

Problem: Using the Monte Carlo method, calculate the mathematical constant e . Do not compute $(1 + 1/n)^n$, calculate the series $\sum 1/n!$, use the logarithm function, etc...

Solution 1: Here's a brilliant and well-established solution. Just repeatedly sample from a uniform random distribution from 0 to 1 and add the sampled numbers. Stop when the sum exceeds 1. The mean number of samples for this process is e . This works because the probability that $x_1 + x_2 + \dots + x_n \leq 1$ is the volume of a simplex $1/n!$, so when you compute the expectation value of the number of samples, this is equivalent to the infinite series expression for e .

Solution 2: Here's a solution that I came up with that I think is more intuitive, but I don't know how sound all the logic is. Imagine we have a bunch of radioactive particles. When a radioactive particle decays, it emits a photon and somehow becomes a new radioactive particle with exactly the same properties (i.e. it can decay again with the exact same rate). This system models a Poisson process with photon emissions at a constant rate, since the population of radioactive particles does not decrease. We run a stopwatch from time $t = 0$ to $t = 1$, and suppose N photons are emitted at random times uniformly across the time interval. We assume N is large, so $N \approx \lambda$, the photon emission rate.

The time at which each photon is emitted can be modeled by sampling from a random uniform distribution N times (since the system respects time-translation symmetry). Then, if we order the sampled times, and we take the difference between consecutive times, we have $N - 1$ time differences Δt_i . Since this is a Poisson process, these time differences must follow the exponential distribution with mean $1/\lambda$. The cumulative distribution function is $1 - e^{-\lambda \Delta t}$, so if there are R time differences that are smaller than the mean, $R/N = 1 - e^{-1}$, or $e = 1/(1 - R/N)$. I've approximated $N - 1$ as N .

We also get $\ln(2)$ for free because the median of the time differences is $\ln(2)/\lambda$.

Here is a Python script for this simulation:

```
1 import numpy as np
2
3 def simulate_photon_emissions(N: int) -> tuple[np.ndarray, float, float]:
4     """Given N photon emissions, return the time differences
5     between consecutive photon emissions, an estimate for e,
6     and an estimate for ln(2)"""
7     samples = np.random.uniform(0, 1, N)
8     samples.sort()
9     differences = np.diff(samples)
10    e = 1/(1-(differences <= 1/N).sum()/N)
11    ln2 = np.median(differences) * N
12    return differences, e, ln2
13
14 N = 100_000_000
15 differences, e, ln2 = simulate_photon_emissions(N)
16
17 print(f"""The computed e is off by a factor of {(e-np.e)/np.e},
18 and ln(2) is off by a factor of {(ln2-np.log(2))/np.log(2)}""")
```

We can also compare the sampled time differences against the exponential distribution just to check that they are the same:

```
1 import matplotlib.pyplot as plt
2
3 plt.hist(differences, bins=50, density=True, alpha=0.6, color='g',
4          label='Time Difference Between Photon Emissions')
5 x = np.linspace(0, np.max(differences), 1000)
6 exp_pdf = N * np.exp(-N * x)
7 plt.plot(x, exp_pdf, 'r-',
8          label=f'Exponential Distribution with Rate {N}'))
9 plt.xlabel('Time Difference')
10 plt.ylabel('Density')
11 plt.legend()
12 plt.show()
```

As a side note, if we wanted a Monte Carlo calculation of $\ln(2)$, a simpler solution would be to exploit $\ln(2) = \int_1^2 dx/x$. One simply samples from a uniform random distribution between 1 and 2, takes the reciprocal of the numbers, and then finds the mean. One can then extend this idea to get a Monte Carlo calculation of e by using a binary search to find t such that $\int_1^t dx/x = 1$.