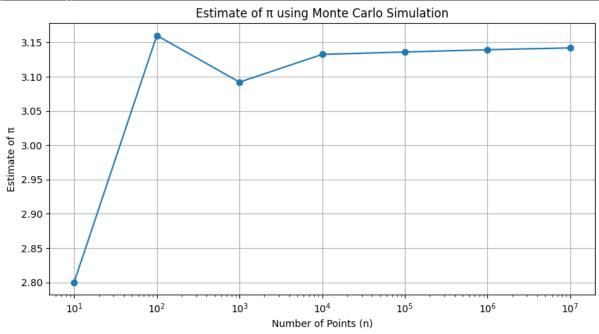
```
import random
import matplotlib.pyplot as plt
def estimate_pi(n):
    count = 0
    for _ in range(n):
        x, y = random.uniform(-1, 1), random.uniform(-1, 1)
        if x**2 + y**2 <= 1:
            count += 1
    return 4 * count / n
# Testing the function
ns = [10, 100, 1000, 10000, 1000000, 1000000] # Different values of n
pi_estimates = [estimate_pi(n) for n in ns]
# Plotting
plt.figure(figsize=(10, 5))
plt.plot(ns, pi_estimates, marker='o')
plt.xscale('log')
plt.xlabel('Number of Points (n)')
plt.ylabel('Estimate of \pi')
plt.title('Estimate of \pi using Monte Carlo Simulation')
plt.grid(True)
plt.show()
```



```
# Assuming use of a simple print statement for tabular data in Python:
print("n", "4*count/n")
for n, pi_estimate in zip(ns, pi_estimates):
    print(n, pi_estimate)
```

n 4\*count/n 10 2.8 100 3.16 1000 3.092 10000 3.1324 100000 3.13592 1000000 3.13922

## **Observations**

- \* As n increases, the estimates of  $\pi$  generally become more accurate and consistent
- \* The variability in the estimate decreases with larger n due to the law of large numbers, which states that as a sample size grows, its mean gets closer to the average of the whole population.
- \* Initially, for small n, the estimates might be highly erratic due to insufficient sampling.

The simulation effectively demonstrates the power of random sampling to estimate mathematical constants and the importance of large sample sizes in achieving high precision in probabilistic simulations. It is a Monte Carlo simulation.