

1 Abstract

- estimation of Fibonacci numbers via golden mean
- eigenvalue and eigenvector and matrix diagonalization

2 Problem

Fibonacci numbers are defined recursively by

$$F_0 = 0, F_1 = 1, F_{n+1} = F_n + F_{n-1}, \forall n \geq 2.$$

What is F_{100} ? Our answer to this problem is surprisingly simple:

$$F_{100} = [\lambda_1^{100} / \sqrt{5}]$$

where $[a]$ means integer part of a and

$$\lambda_1 = \frac{1 + \sqrt{5}}{2}.$$

3 Analysis

Consider the following question:

- You shoot a square $(-1, 1)^2$. Suppose your shot is uniform in this square, then what is the probability you have a successful shot? We say “your shot is successful”, if your shot belongs to the unit ball B_1 .

The answer is

$$\text{Prob of succesful shot} = \frac{\text{Area of } B_1}{\text{Area of } (-1, 1)^2} = \frac{\pi}{4}.$$

This means that, as long as one can approximate probability of successful shot, one can approximate π by multiplying 4. This can be done by computer:

- Simulate many uniform shots, and compute the ratio of successful shots.

Pseudocode for `pi_mc(N)`:

- Generate N iid points

$$\{(X_i, Y_i) : i = 1, 2, \dots, N, X_i, Y_i \sim U(-1, 1)\};$$

- Count n , the number of points satisfying

$$X_i^2 + Y_i^2 < 1.$$

- Compute

$$\hat{\pi} = 4 \cdot \frac{n}{N}.$$

4 Monte Carlo basics

4.1 Bias and MSE

One can implement above approximation multiple times and observe that

- (random estimator) Target value π is deterministic, but each implementation gives different outcome $\hat{\pi}$;
- (Convergence) Each obtained outcome, as long as N is large enough, gives some close approximation.

We are going to generalize our observations in this below.

- A random estimator $\hat{\alpha}$ to a deterministic value α is called as Monte Carlo (MC) approximation.
- Moreover, we define

$$Bias = \mathbb{E}[\hat{\alpha}] - \alpha$$

and

$$MSE = \mathbb{E}[(\hat{\alpha} - \alpha)^2].$$

- If Bias is zero, then we call this as unbiased MC.

Proposition 1 $MSE(\hat{\alpha}) = |Bias(\hat{\alpha})|^2 + Var(\hat{\alpha})$. In particular, if $\hat{\alpha}$ is unbiased, then MSE is Variance.

PROOF: ... \square

Although seemingly absurd, we consider the above estimator with $N = 1$, which is equivalent to

- Consider

$$\hat{\alpha} = 4I(X_1^2 + Y_1^2 < 1), \quad X_1, Y_1 \sim U(-1, 1)$$

as MC for π . Then the outcome is either 0 or 4. In any case, it is a bad approximation.

- However, we can show that it's an unbiased MC. (why?)
- Find MSE?

4.2 Ordinary Monte Carlo

Unbiased MC is very desirable, because one can employ crude (ordinary) MC to make it more accurate: ¹

- Suppose $\hat{\alpha}$ is a square integrable unbiased MC;
- Obtain N independent replicates

$$\{\hat{\alpha}_i : i = 1, \dots, N\}.$$

¹We say a random variable X is in L^p , if its p th moment exists, i.e.

$$\mathbb{E}X^p < \infty.$$

If $X \in L^2$, then we say it's square integrable.

- Taking their average, it gives a new MC:

$$\beta_N = \frac{1}{N} \sum_{i=1}^N \hat{\alpha}_i.$$

- β_N is unbiased again. (why?)
- $MSE(\beta_N) = \frac{1}{N} MSE(\hat{\alpha}) \rightarrow 0$. (why?)
- β_N is almost surely consistent, (why?) i.e.

$$\mathbb{P}(\lim_N \beta_N = \alpha) = 1.$$

- β_N is L^2 -consistent, (why?) i.e.

$$\mathbb{E}(\beta_N - \alpha)^2 \rightarrow 0.$$

As a conclusion, one can always use crude MC to make better approximation provided there exists an unbiased MC $\hat{\alpha}$, which is obtainable in sacrifice of higher computational cost. Given a fixed amount of computational cost, to improve the efficiency, it is essential to reduce $Var(\hat{\alpha})$ as much as possible.

Ex. Given i.i.d $\{\alpha_i : i \in 1, 2, \dots, N\}$, we use

$$\beta_N = \frac{1}{N} \sum_{i=1}^N (\alpha_i - \bar{\alpha})^2$$

as the estimator of $Var(\alpha_1)$, where $\bar{\alpha} = \frac{1}{N} \sum_{i=1}^N \alpha_i$. Suppose $\alpha_1 \in L^2$, then

- Prove it is biased.
- Prove that it is consistent in L^2 .
- Can you propose an unbiased estimator?

Ex. Prove that L^2 consistency implies consistency in probability.

Prj. Investigate the convergence rate of `pi_mc(N)`.

- Repeat $m = 100$ times:
For $N \in \{2^n : n = 5, \dots, 10\}$: Run `PiMc(N)`
- approximate their MSE for each N with m computations;
- plot log-log chart and approximate its convergence order.

Ex. Can you improve the MC for π ? Hint: antithetic variate method

Ex. Can you propose a deterministic approximation to π ?