

Monte Carlo Integration

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Introduction

Beyond being able to generate random variables, we should also be able to apply these simulation methods to solve more complex problems. We'll begin with Monte Carlo Integration methods.

Topics to be covered:

1. Classic Monte Carlo Integration
2. Importance Sampling
3. Importance Sampling Resampling

Monte Carlo Integration

Given a function $g(x)$ for which we wish to integrate over $[a, b]$, $\int_a^b g(x)dx$, we can treat this deterministic problem as a stochastic one to find the solution. Treat X as if a random variable with density $f(x)$, then the mathematical expectation of the random variable $Y = g(X)$ is

$$E[g(X)] = \int_{\mathcal{X}} g(x)f(x)dx$$

If a random sample X_1, \dots, X_n is generated from $f(x)$, an unbiased estimator of $E[g(X)]$ is the sample mean.

$$\bar{g}_n = \frac{1}{n} \sum_{i=1}^n g(x_i)$$

As an example, suppose we have a function $g(x) = 3x^2$ for which we wish to integrate over the interval 0 to 2. We could apply deterministic numerical approximation methods (see R's `integrate`) or we could treat x as a random variable from a $Unif(0, 2)$ whose pdf is simply $f(x) = \frac{1}{2-0} = \frac{1}{2}$. If we now generate some $N = 1,000$ random values from $f(x)$ and evaluate them at $g(x)$, then take the mean, we'd be calculating the expected value of $g(x)$,

$$\Xi = \int_0^2 g(x)dx = \left(\frac{2-0}{2-0}\right) \times \int_0^2 g(x)dx = 2 \times \int_0^2 g(x) \frac{1}{2} dx = 2 \times E[g(X)] = 2 \times \int_{-\infty}^{\infty} g(x)f(x)dx \approx 2 \times \frac{1}{n} \sum_{i=1}^n g(x_i) \approx v$$

If we now simulate this, we will see we approximate the true solution $\int_0^2 g(x)dx = 8$

```
N = 10000 ## sample size

g <- function(x) { 3*x^2 } ## function of interest, g(x)

X <- runif(n = N, min = 0, max = 2) ## samples from f(x)

v = 2 * mean(g(X)) ## 2 * E[g(x)]

print(v) ## approximately 8

## [1] 7.983917
```