

Multi-dimensional integration and Monte-Carlo integration

Why multi-dimensional integration is hard

Direct integration

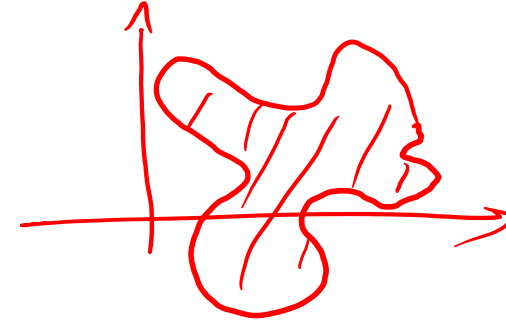
Monte-Carlo integration

Sampling: the big problem with Monte-Carlo integration

Solutions to this problem

- quasi-random numbers
- stratified sampling
- importance sampling

Why multi-dimensional integration is hard:



1. It can scale really badly:

If for a 1D integral you need 100 points in a quadrature evaluation,
For a 2D integral you need 100^2 points, for a 3D integral you need 100^3 points, and so on

2. Boundaries become really complicated.

3

1. It is (often) difficult to know, in ND space, *where the maximum contributions to the integral come from*

Nested Integration

This is the only reliable option if you need to evaluate an N-D integral to numerical precision.

The idea is that you integrate over one dimension at a time,
Using your 1D quadrature.

A simple domain in (say) 3D can be written

$$D = \{ (x, y, z) \mid a \leq x \leq b, \quad g_l(x) \leq y \leq g_u(x), \quad u_1(x, y) \leq z \leq u_2(x, y) \}$$

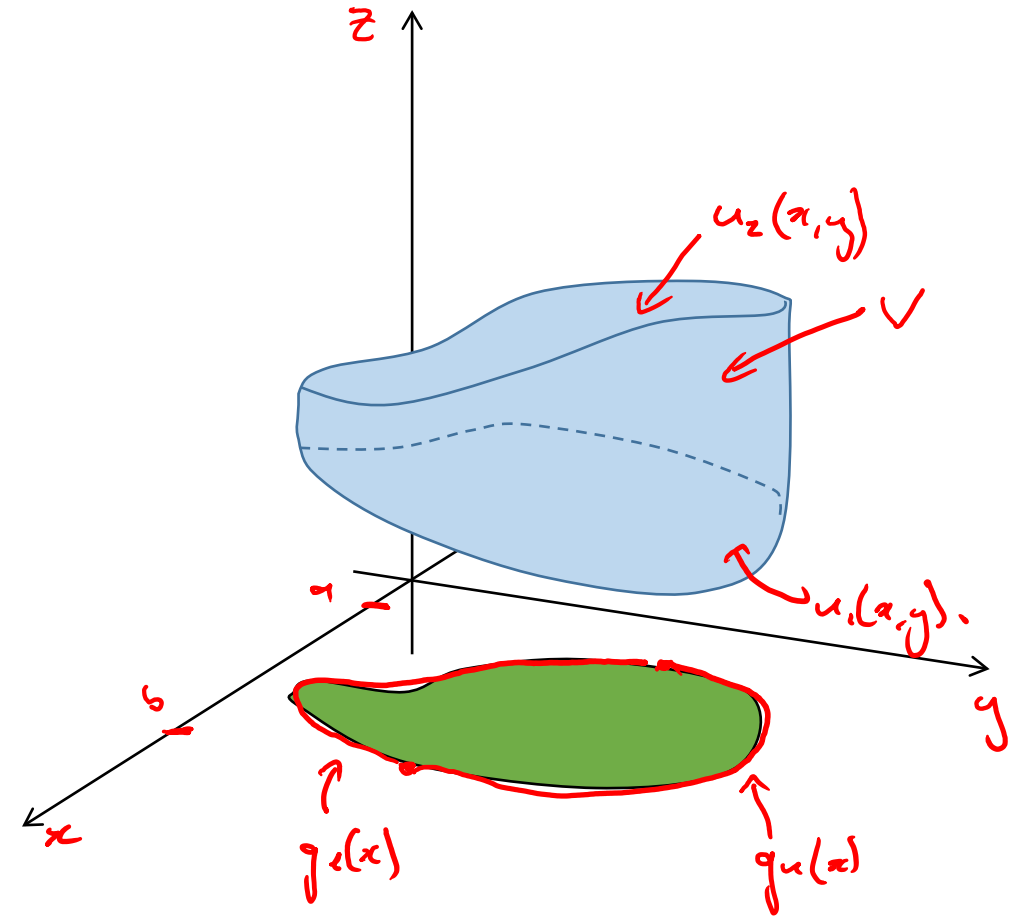
Handwritten red annotations: A bracket on the right side of the set definition is labeled "curve".

The integral in 3D over this domain is then

$$\iiint_V f(x, y, z) dx dy dz = \int_a^b \left[\int_{g_l(x)}^{g_u(x)} \left[\int_{u_1(x, y)}^{u_2(x, y)} f(x, y, z) dz \right] dy \right] dx$$

Handwritten red annotations:

- "first" points to the outermost integral \int_a^b .
- "second" points to the middle integral $\int_{g_l(x)}^{g_u(x)}$.
- "third" points to the innermost integral $\int_{u_1(x, y)}^{u_2(x, y)}$.
- "function of x " points to the dx term.
- "function of (x, y) " points to the dy term.
- "function of (x, y, z) " points to the integrand $f(x, y, z)$.



Code structure for nested integration can be a bit subtle, because you need to return a function as the answer to the inner integrals.

Nested integration over x,y

Function yint(f,x,c,d)

For the given value of x, integrate f(x,y) over y between c and d using 1D quadrature, call this yint

return yint

- Define limits for x as [a,b]
- Define limits for y as [c,d]
- Result = integration of yint(f,x,c,d) over x between a and b using 1D quadrature

Note:

For most programming languages, You'll have to define "dummy" functions

$f_1(y) = f(x,y)$ with a fixed x

to do this step, and another "dummy function"

$f_2(x) = \text{yint}(f,x,c,d)$ with a fixed f, c and d

To do this step.

Nested quadrature is:

- Reliable | ✓
- Accurate | ✓
- Complicated | ✗
- Slow | ✗

Is there a method that scales better for higher dimensions,
even if it means sacrificing some accuracy? ||

Monte Carlo Integration

To find the integral

$$\int_a^b f(x) dx$$

We previously *approximated the function* with something that is easier to integrate.

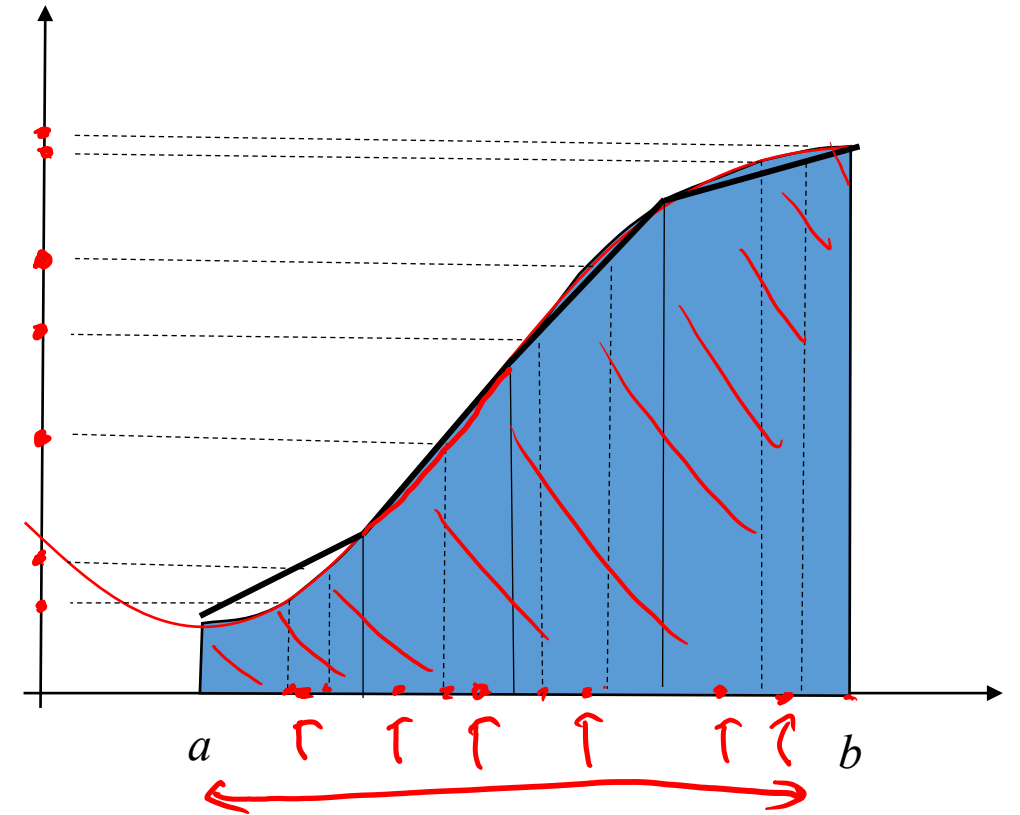
However we could also view the integral as the *expected value of f if we sampled it over a large number of points*.

$$E(f) = \frac{1}{N} \sum_{i=1}^N f(x_i)$$

As the number of sampling points increases,

$$E(f) \rightarrow \frac{1}{b-a} \int_a^b f(x) dx$$

In accordance with *the Law of Large numbers*.



$$\frac{1}{N} \sum_{i=1}^N f(x_i) = \frac{1}{b-a} \int_a^b f(x) dx \quad \text{as } N \rightarrow \infty.$$

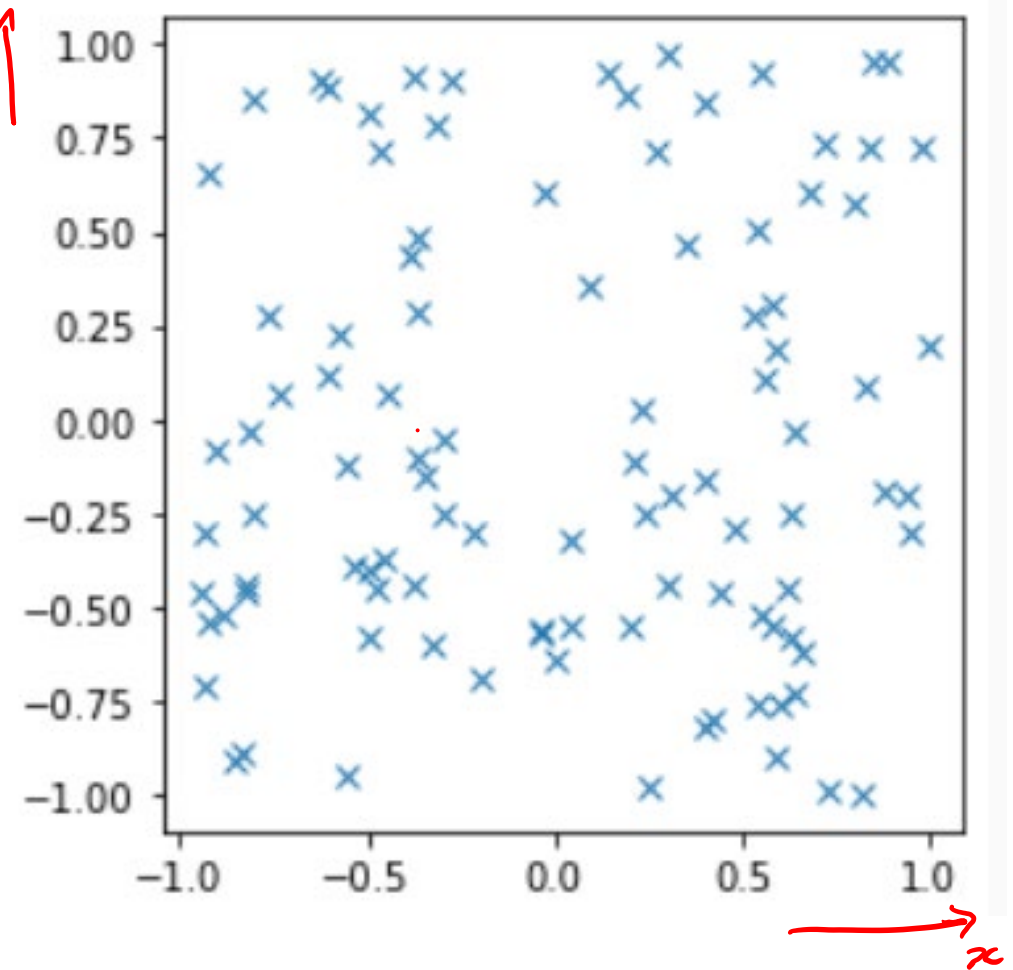
For large N we can approximate $\int_a^b f(x) dx \approx \frac{b-a}{N} \sum_{i=1}^N f(x_i)$

This also works in two dimensions:

$$\int_a^b \int_c^d f(x, y) dx dy \approx \frac{V}{N} \sum_{i=1}^N f(x_i, y_i)$$

Handwritten red annotations: "Volume of the domain" with an arrow pointing to V ; two arrows pointing to x_i and y_i in the function argument; a red underline under the summation index $i=1$ to N .

Where V is the size of the region being sampled.

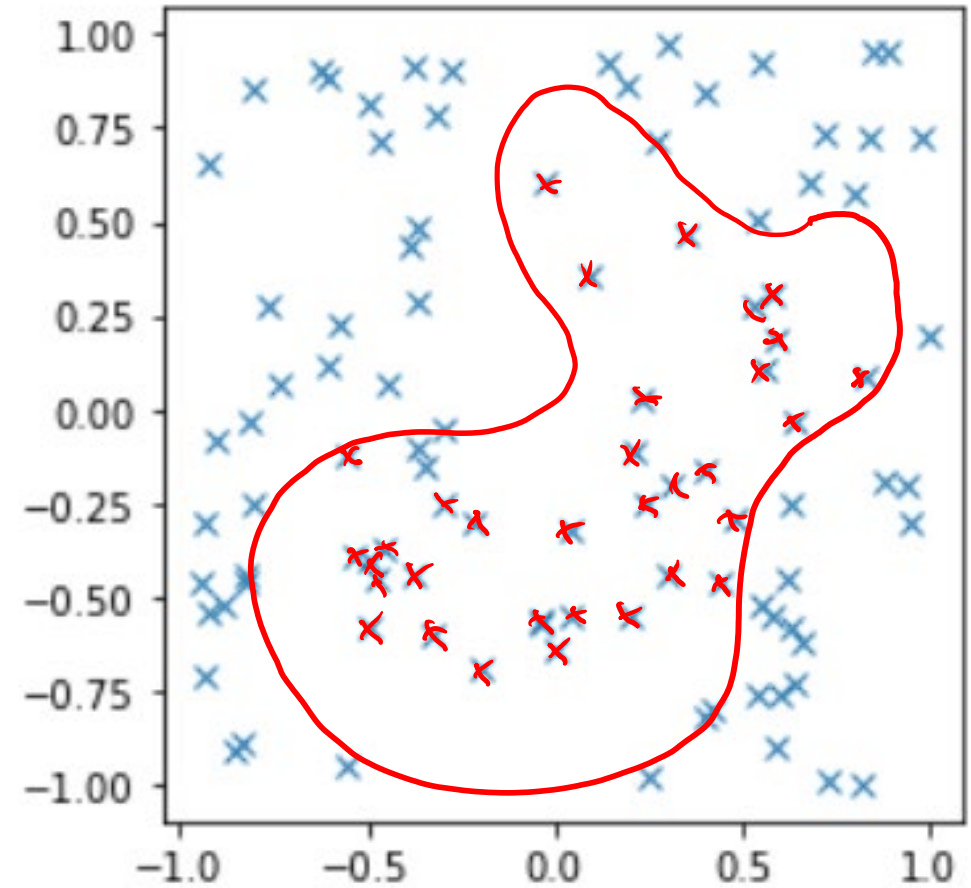


This also works in two dimensions:

$$\int_a^b \int_c^d f(x, y) dx dy \approx \frac{V}{N} \sum_{i=1}^N f(x_i, y_i)$$

Where V is the size of the region being sampled.

This also works for complicated regions:
Just define the function to be zero *outside the region*
that you're interested in.



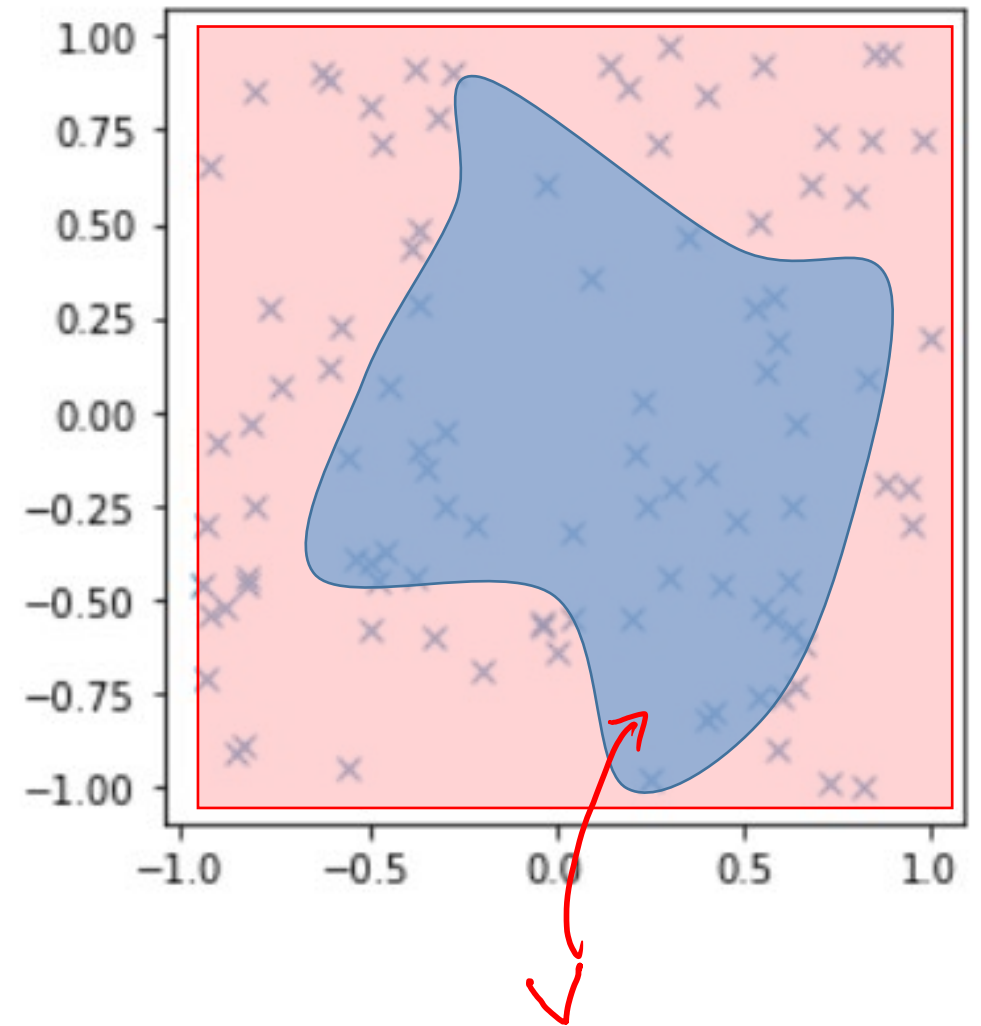
Monte Carlo integration

1. Pick a random sample of points for each of your dimensions
 $p = (x_p, y_p, z_p, \dots)$, which covers your region of integration.

2. The integral is then the sum

$$I \approx \frac{V}{N} \sum_{i=1}^N f(x_i, y_i)$$

Where you only include the points lying in the integration region.
Here V is the volume of the sampling domain.



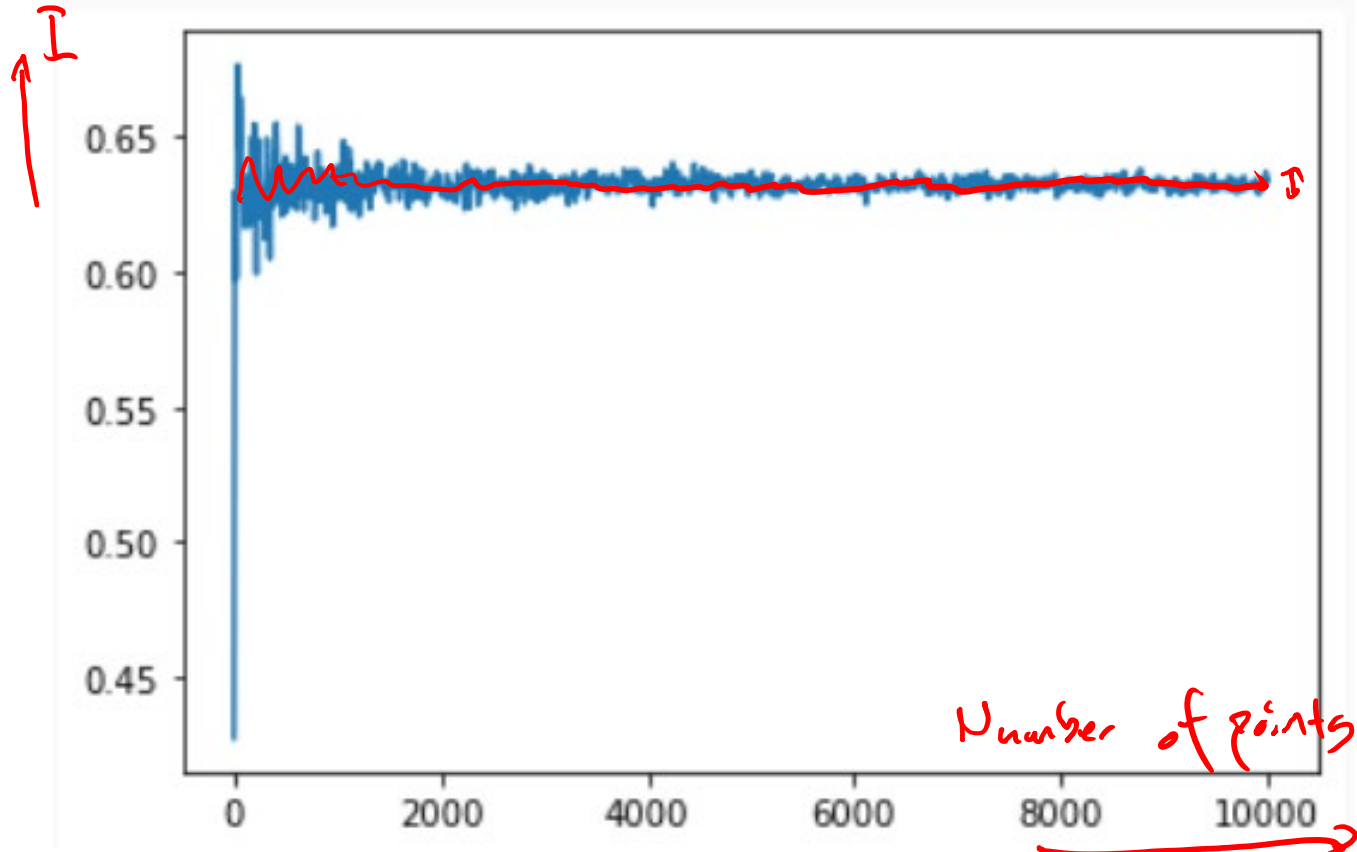
Advantages:

1. Scales with the number of points rather than as the power of the number of dimensions !!

2. Simple to implement

Disadvantages:

Sample variance!



Variance of Monte Carlo:

Let the approximate integral be

$$I_N = \frac{V}{N} \sum_{i=1}^N f(x_i)$$

$$\text{Var}[I_N] = \text{Var}\left[\frac{V}{N} \sum_{i=1}^N f(x_i)\right]$$

$$= \frac{V^2}{N^2} \sum_{i=1}^N \text{Var}[f(x_i)]$$

$$= \frac{V^2}{N^2} \sum_{i=1}^N \sigma_f^2 = \frac{V^2}{N^2} \sigma_f^2 N$$

$$= \frac{V^2}{N} \sigma_f^2 \sim \frac{1}{N}$$

→ Recall:

$$\text{Var}[f(x)] = \sigma_f^2 = \frac{1}{N-1} \sum_{i=1}^N [f(x_i) - E(f)]^2$$

So that:

$$\text{Var}[af(x)] = a^2 \text{Var}[f]$$

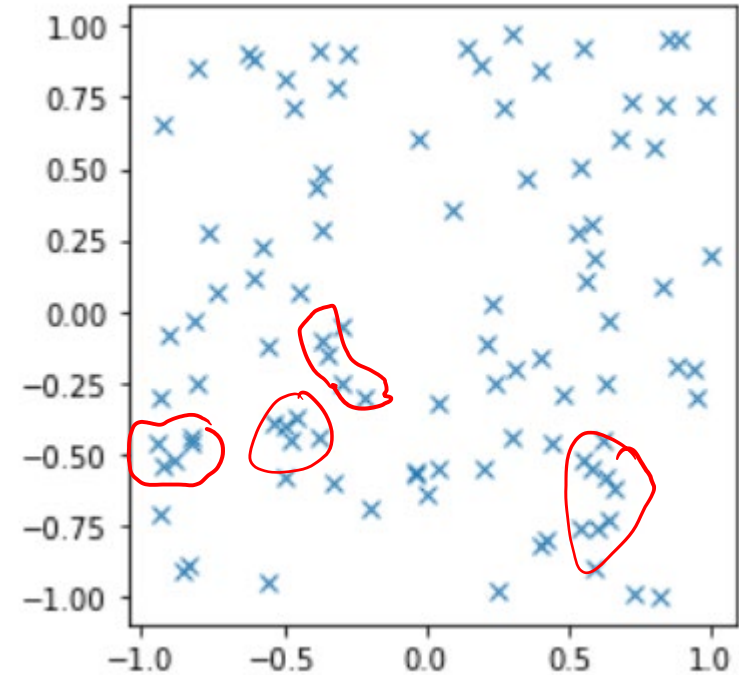


The error in the estimate of the integral decreases as $\sim 1/\sqrt{N}$

Strategies for reducing the variance (and hence the error) revolve around reducing the “clumping” of the random points.

Random numbers clump together in a way not ideally suited For Monte-Carlo integration.

Is there a type of random number that is Random, but not too random?

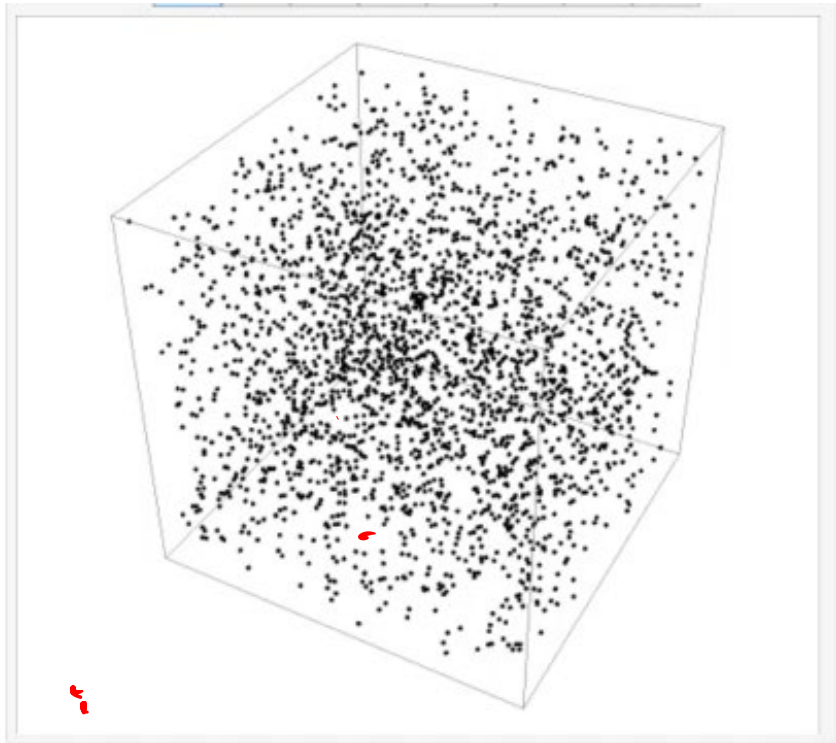


The answer is “yes”: these are known as quasi-random numbers.

Quasi-random numbers vs Pseudo-random numbers

Quasi-random numbers, which aim at a certain level of randomness, should
Not be confused with Pseudo-random numbers, which try to be as random as possible.

Sequences of genuine random numbers are (surprisingly!) difficult
to simulate using computers. Often a sequence that seems random
Ends up having hidden order in it.



The attempt to generate pseudo-randomness is a whole subject in itself! See Chapter 7 of Numerical Recipes for more info.

Quasi-random number sequences

These sequences are also known as “sub-random sequences”; they are random numbers that “avoid each other” to a defined extent.

Important types:

Halton sequences:
(easy to code)

To get the j th number in a Halton sequence:

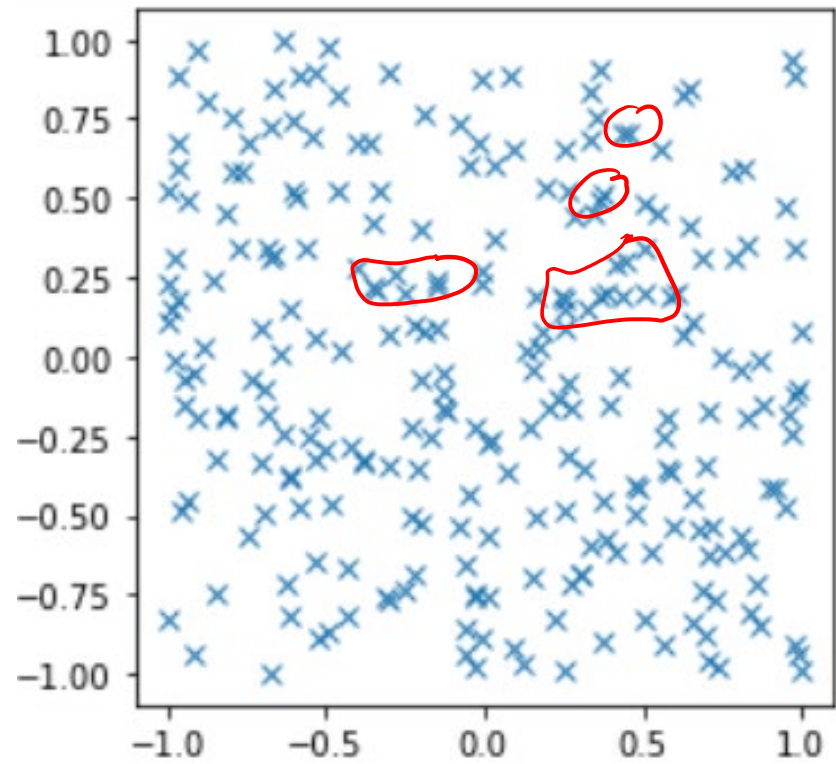
1. Write j as a number in base b , where b is prime
2. Reverse the digits, and put a decimal point in front of the sequence. This is the j th number H_j

Sobol sequences:
(harder to code, but generally better)

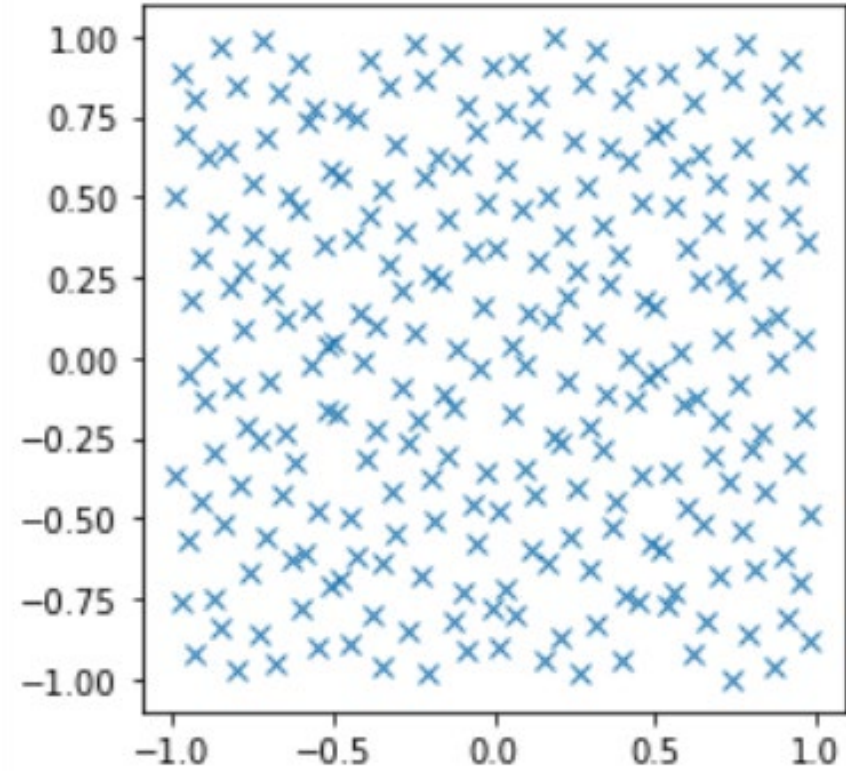
To get the j th number of the Sobol sequence,
We need to compute the *Gray Code* of j $G(j)$, then write it as a binary fraction. It then gets pretty complicated, but let me know if you're interested!

https://en.wikipedia.org/wiki/Sobol_sequence

https://en.wikipedia.org/wiki/Gray_code



pseudo-random

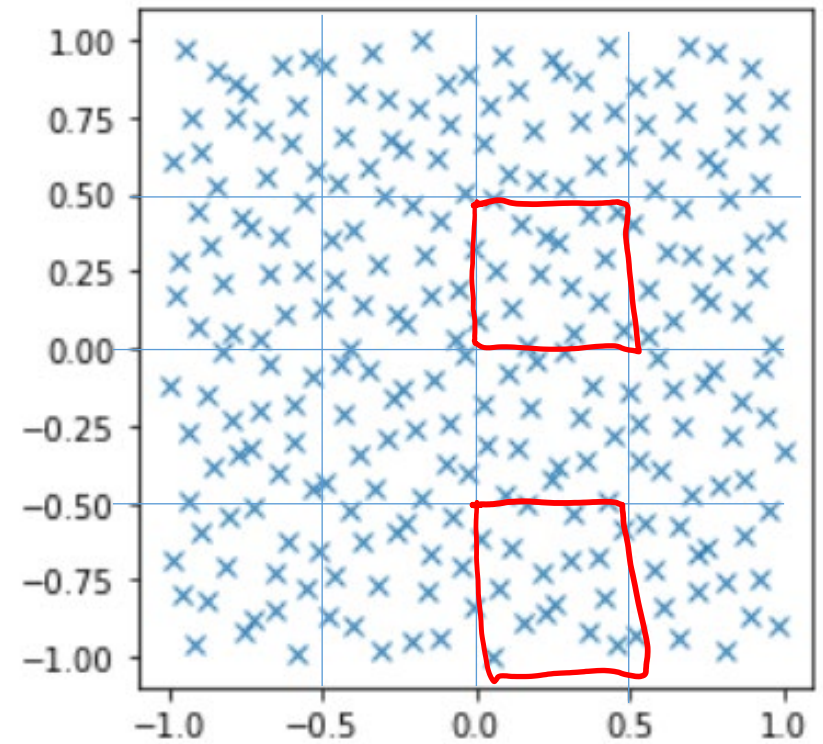
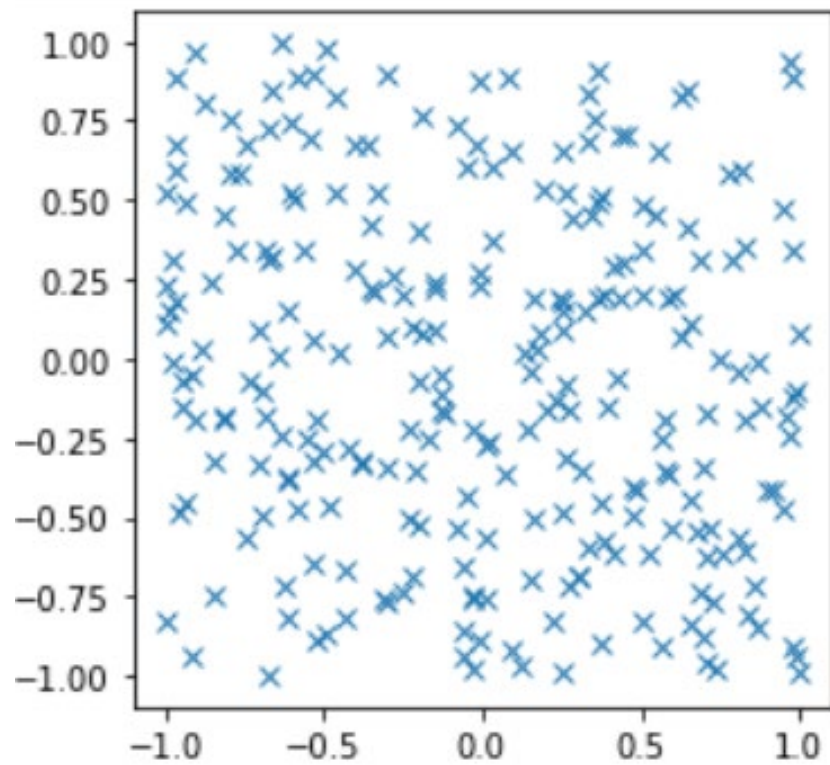


Sobol sequence

Stratification sampling:

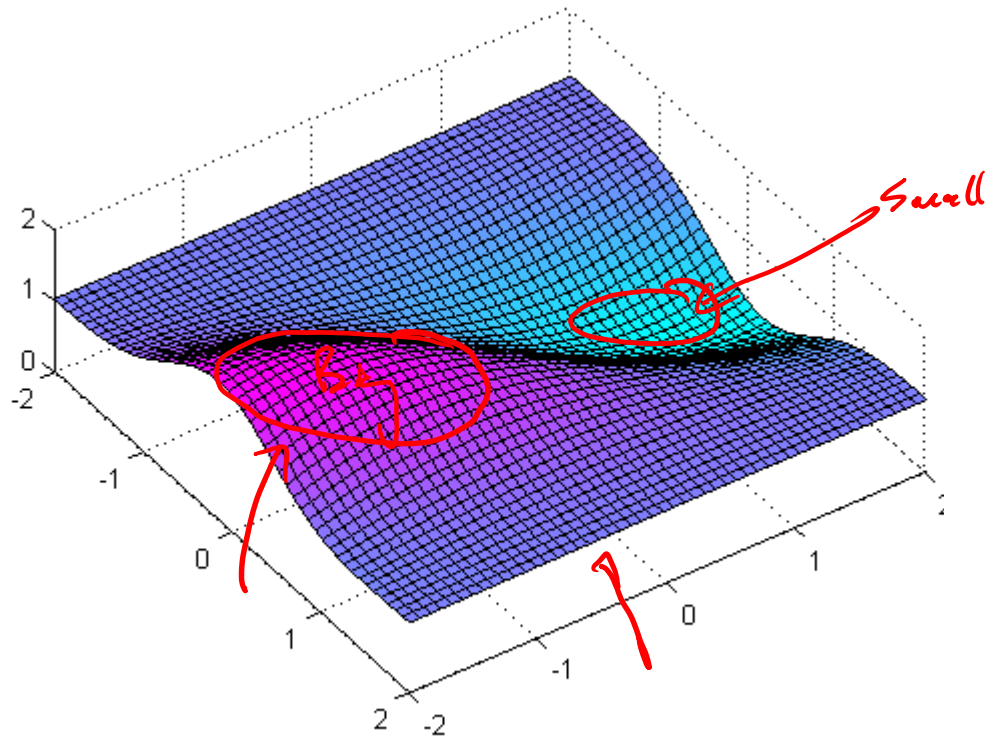
This strategy reduces the sampling variance by (recursively)

Dividing the volume into sub-domains, and sampling only on those domains.



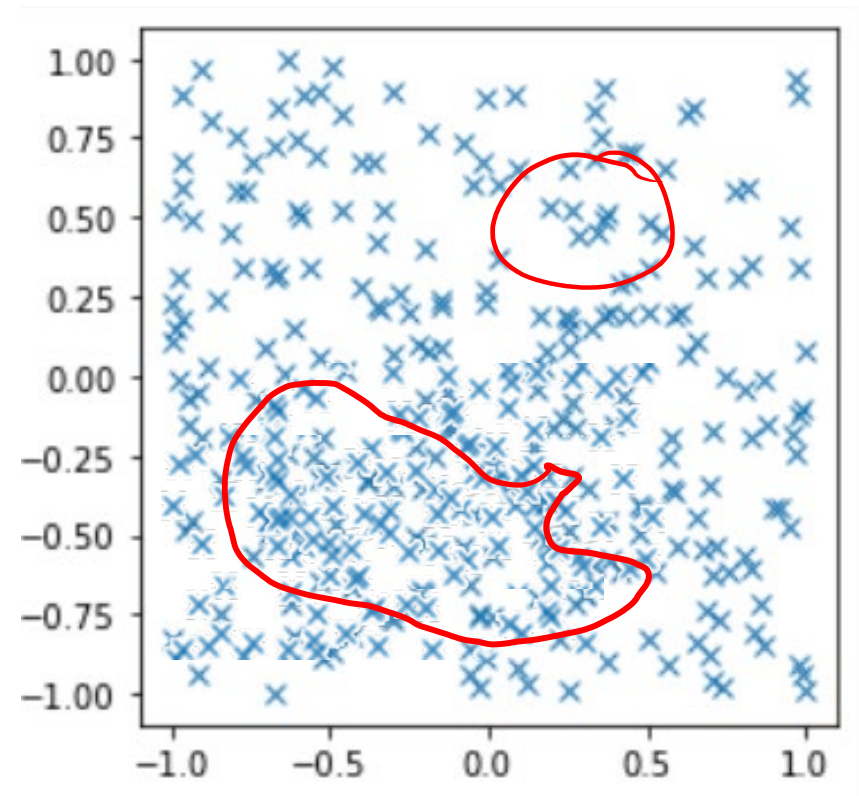
Importance sampling

Put more samples where the function f is bigger:



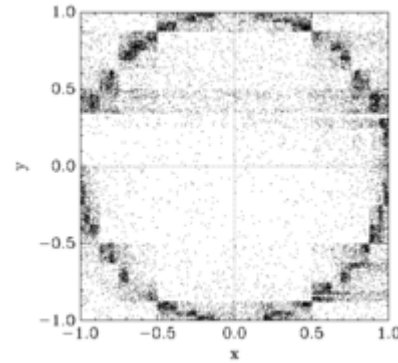
Choose a sampling density p such that

$$p \sim |f|$$



Other strategies:

- Recursive stratified sampling



- Mixed methods (using both stratified sampling and importance sampling)