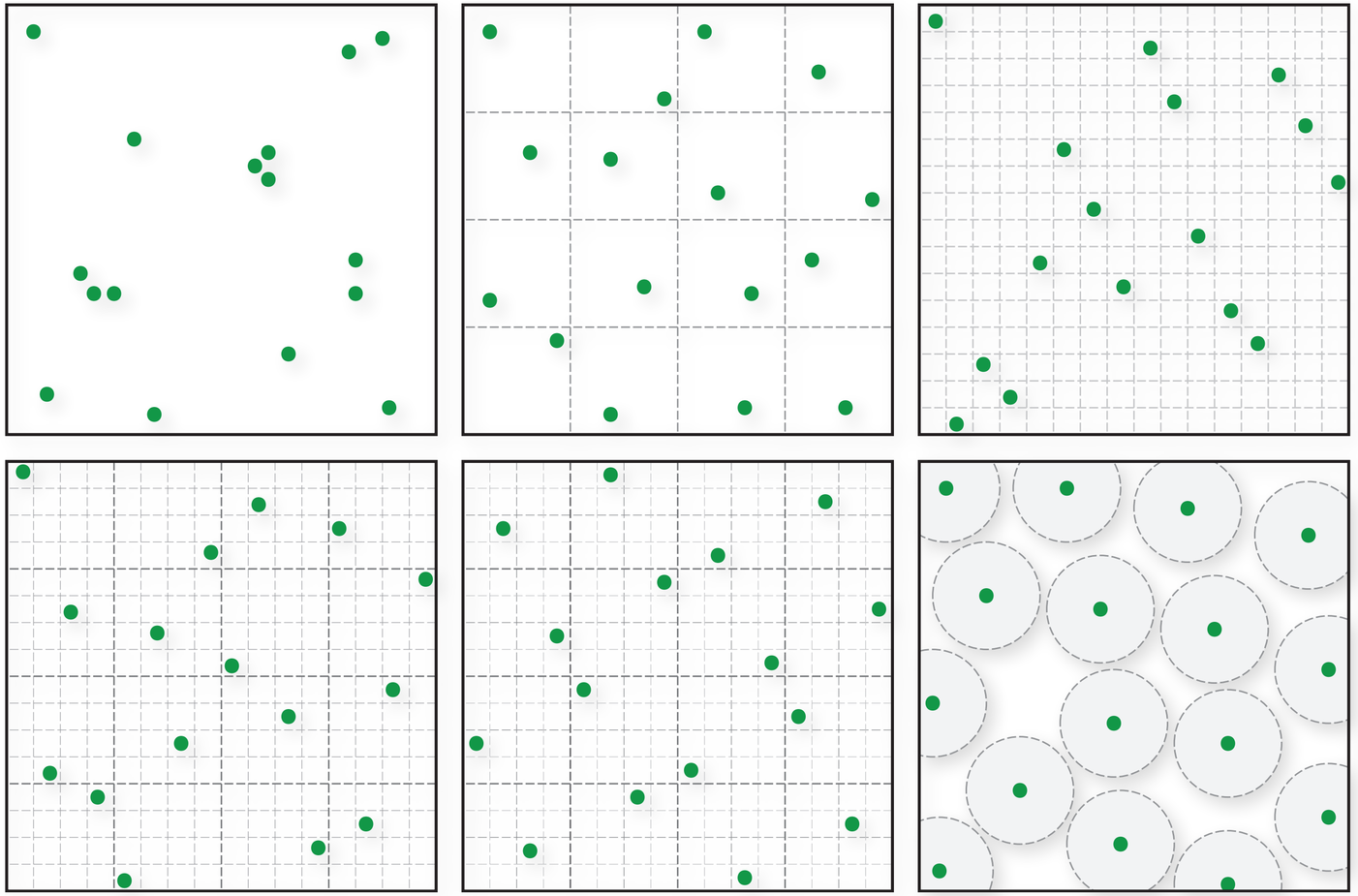
Popular Sampling Patterns

Fourier Analysis of Numerical Integration in Monte Carlo Rendering



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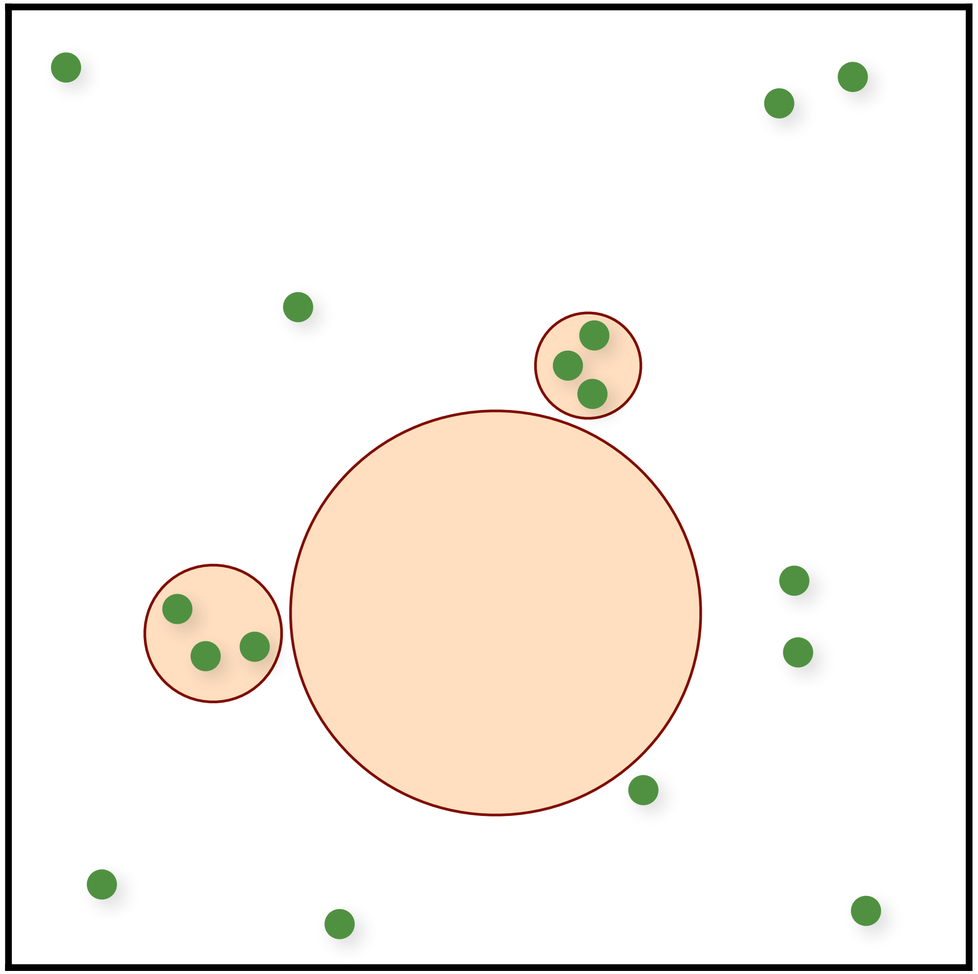
Need some segue/intro slide

Independent Random Sampling

```
for (uint i = 0; i < num; i++)
{
    samples(i).x = randf();
    samples(i).y = randf();
}
```



✔ Trivially extends to higher dimensions

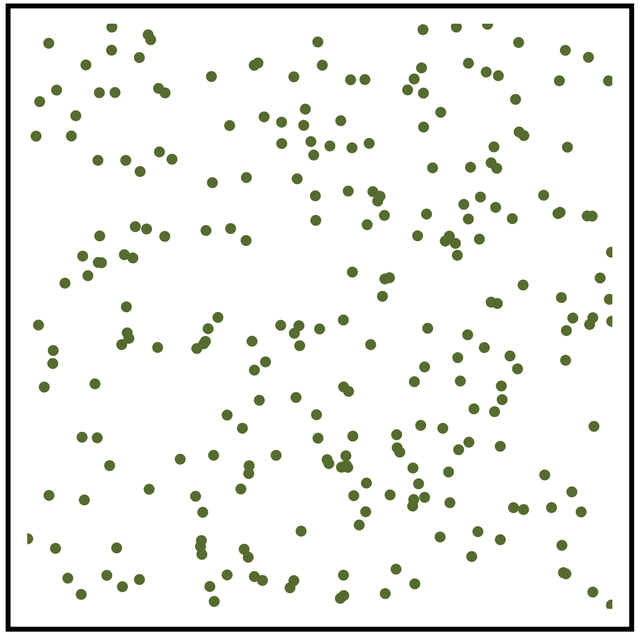
✔ Trivially progressive and memory-less

✘ Big gaps

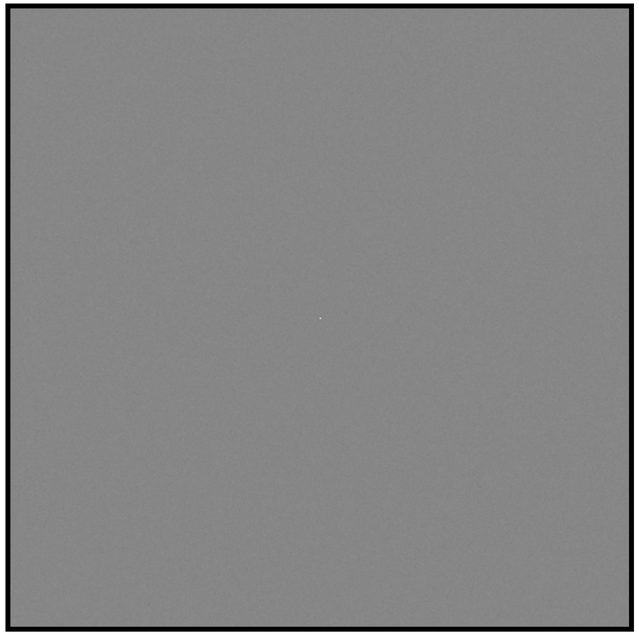
✘ Clumping

Independent Random Sampling

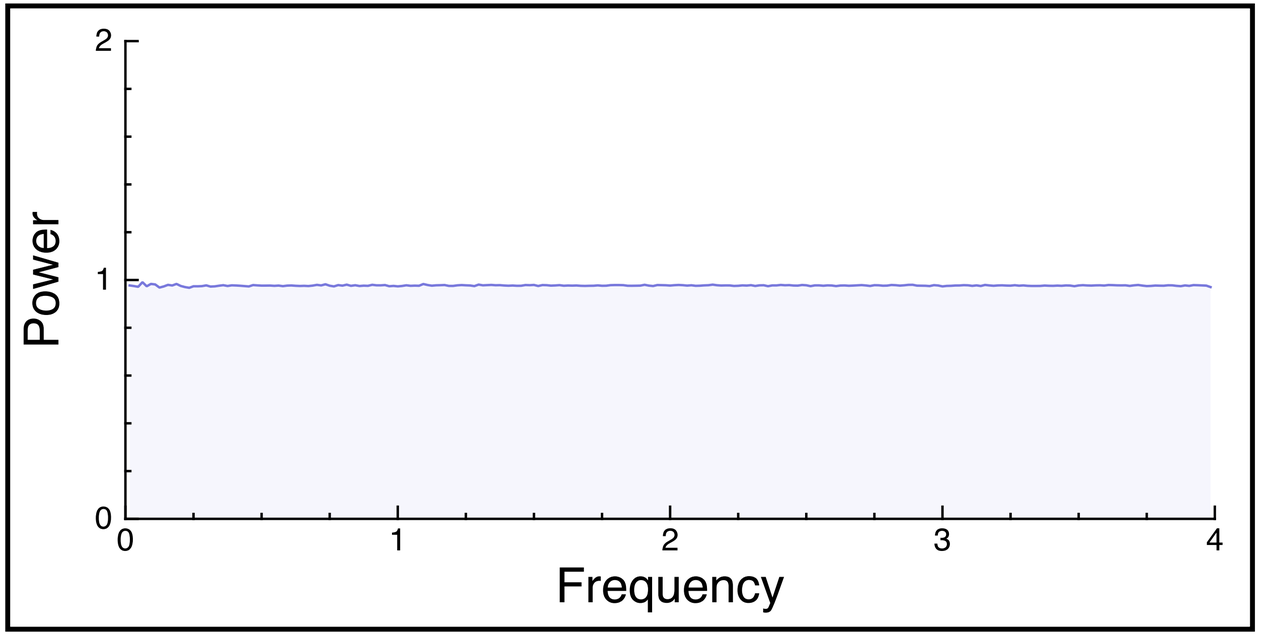
Samples



Power spectrum

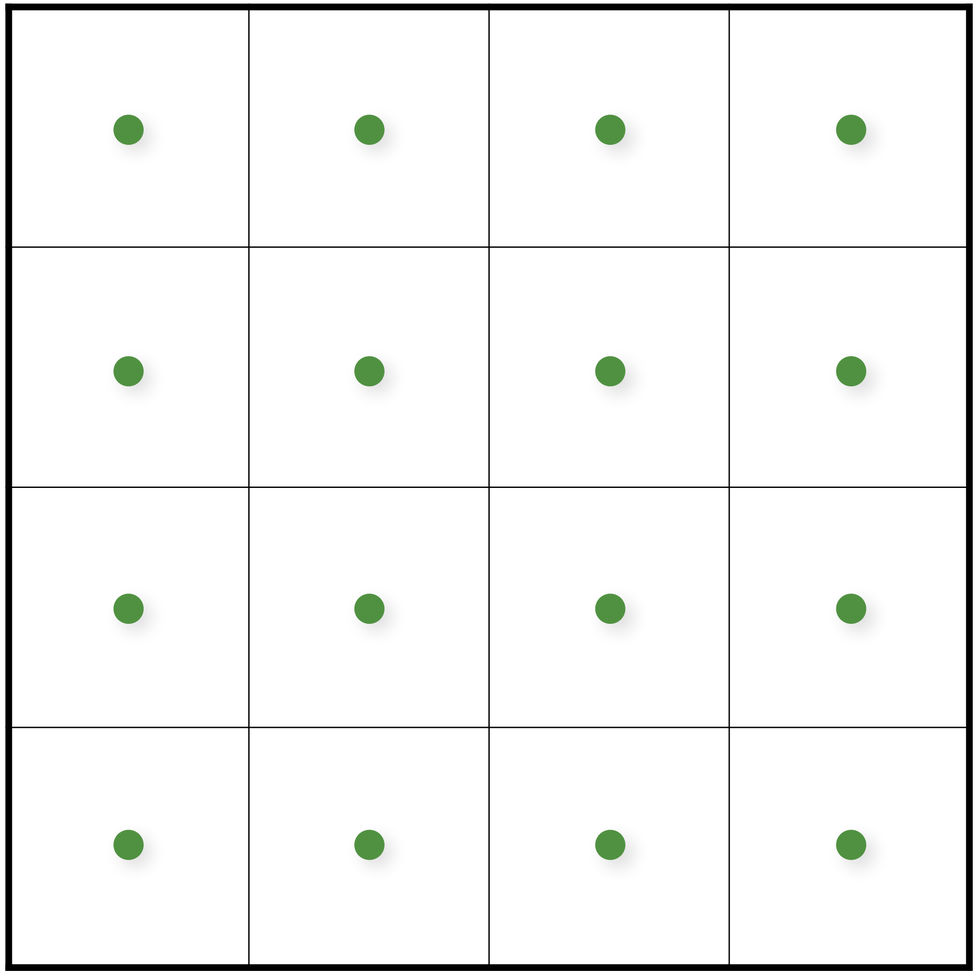


Radial mean



Regular Sampling

```
for (uint i = 0; i < numX; i++)
    for (uint j = 0; j < numY; j++)
    {
        samples(i,j).x = (i + 0.5)/numX;
        samples(i,j).y = (j + 0.5)/numY;
    }
```



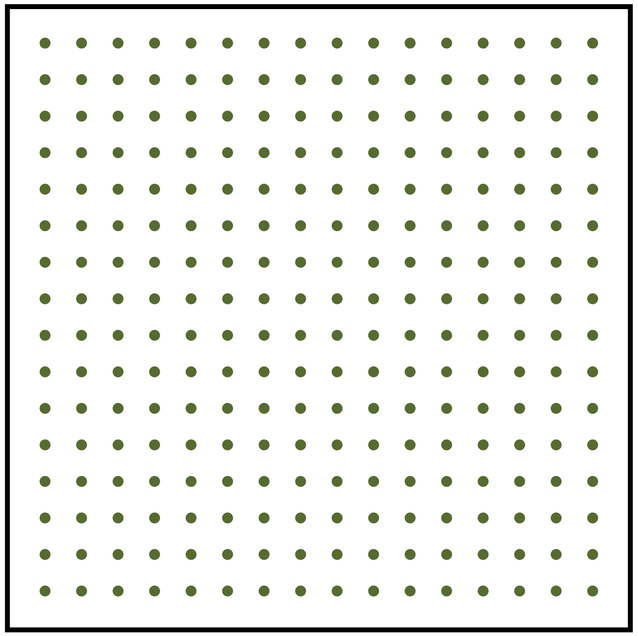
✔ Extends to higher dimensions, but…

✘ Curse of dimensionality

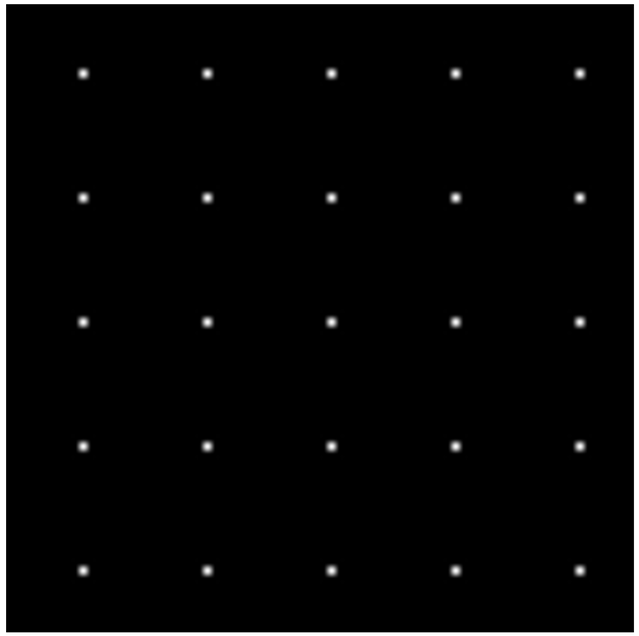
✘ Aliasing

Independent Random Sampling

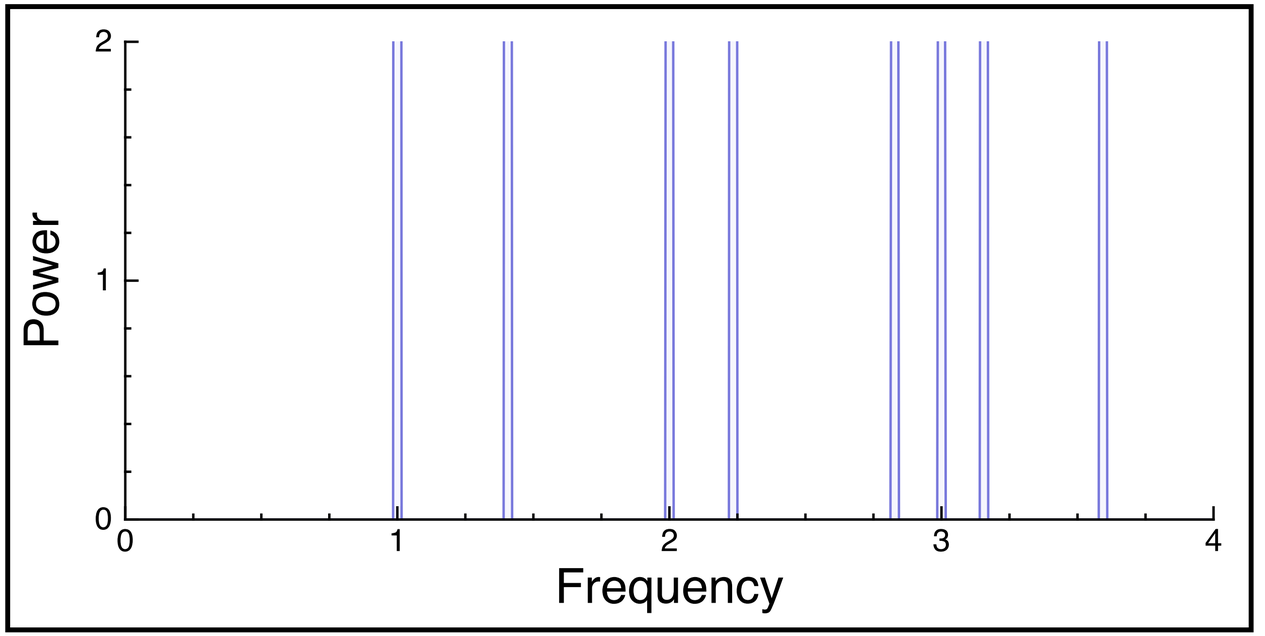
Samples



Power spectrum

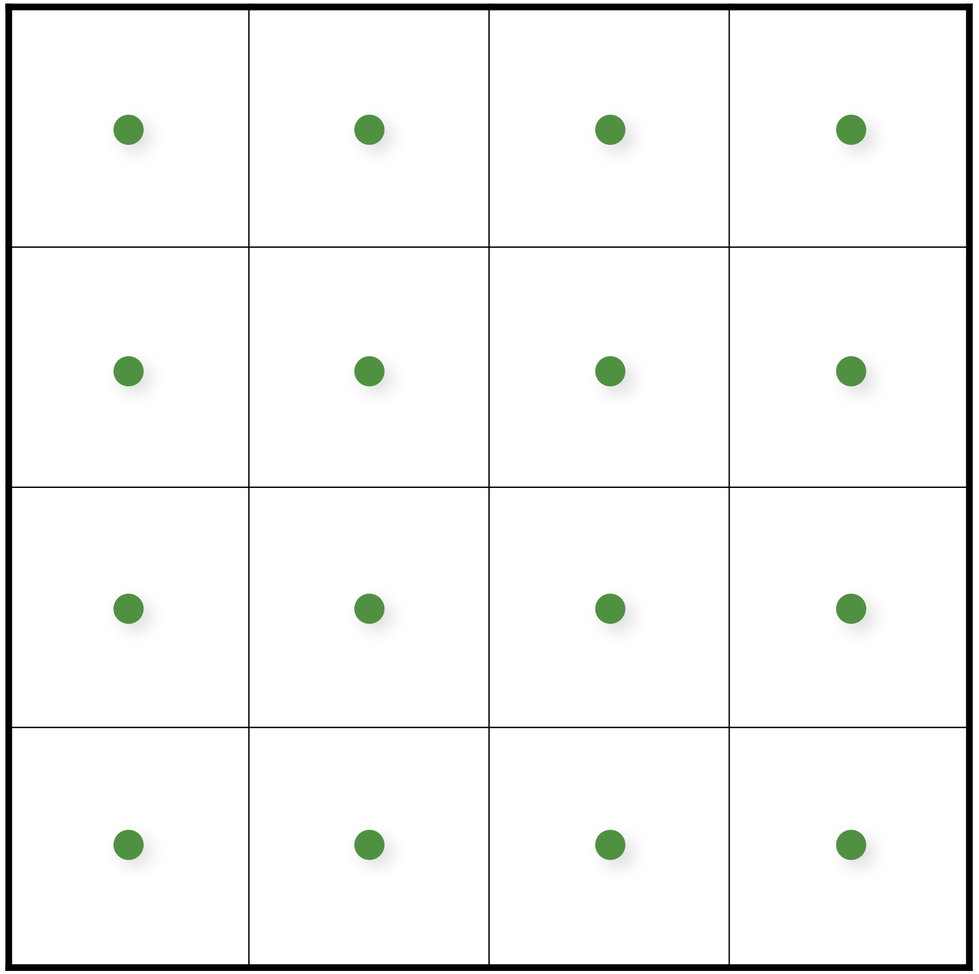


Radial mean



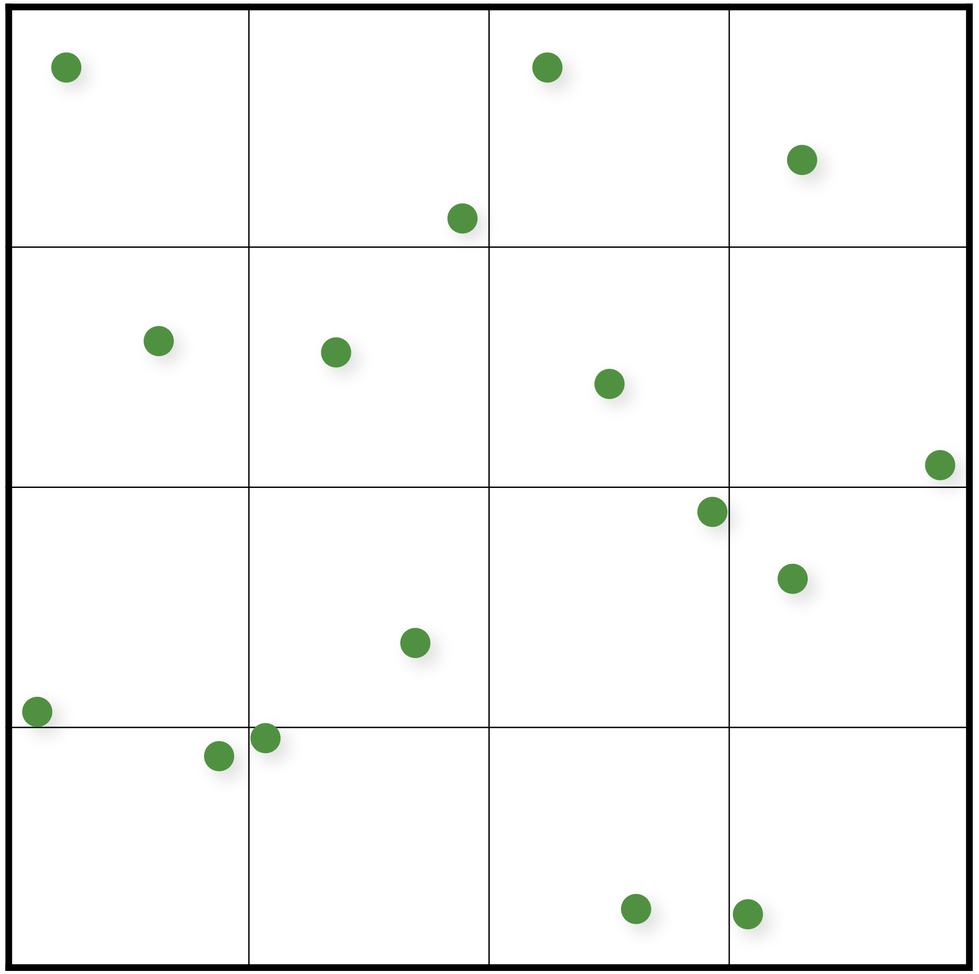
Regular Sampling

```
for (uint i = 0; i < numX; i++)
    for (uint j = 0; j < numY; j++)
    {
        samples(i,j).x = (i + 0.5)/numX;
        samples(i,j).y = (j + 0.5)/numY;
    }
```



Jittered/Stratified Sampling

```
for (uint i = 0; i < numX; i++)
    for (uint j = 0; j < numY; j++)
    {
        samples(i,j).x = (i + randf())/numX;
        samples(i,j).y = (j + randf())/numY;
    }
```



✔ Provably cannot increase variance

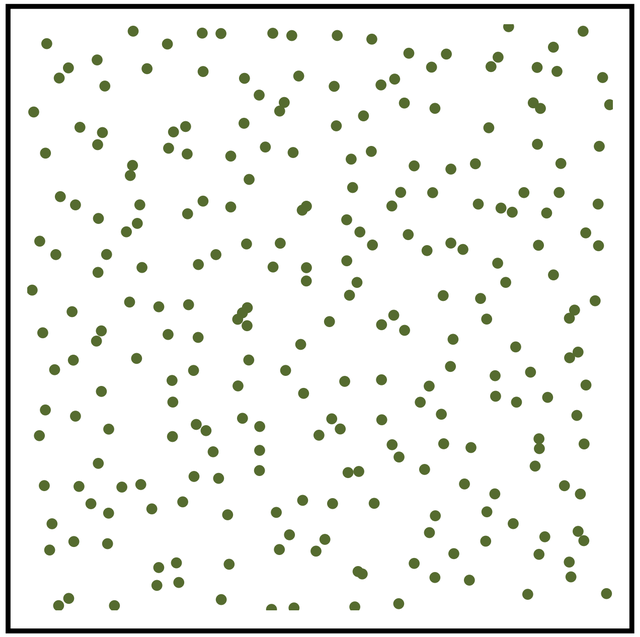
✔ Extends to higher dimensions, but…

✘ Curse of dimensionality

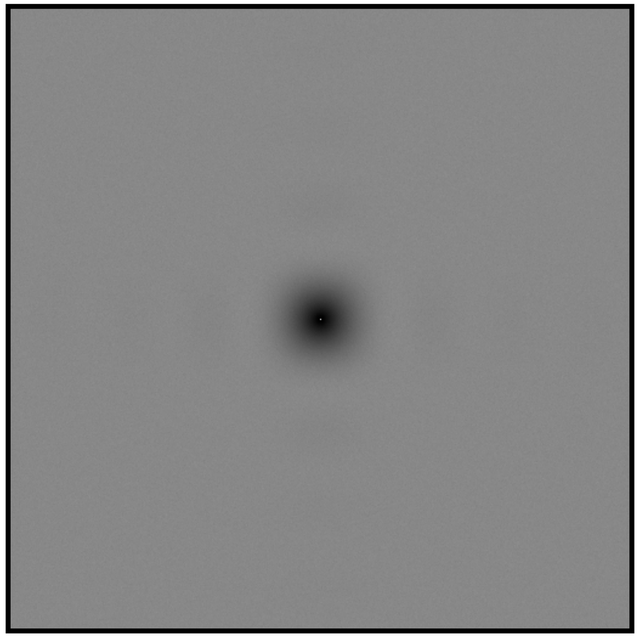
✘ Not progressive

Jittered/Stratified Sampling

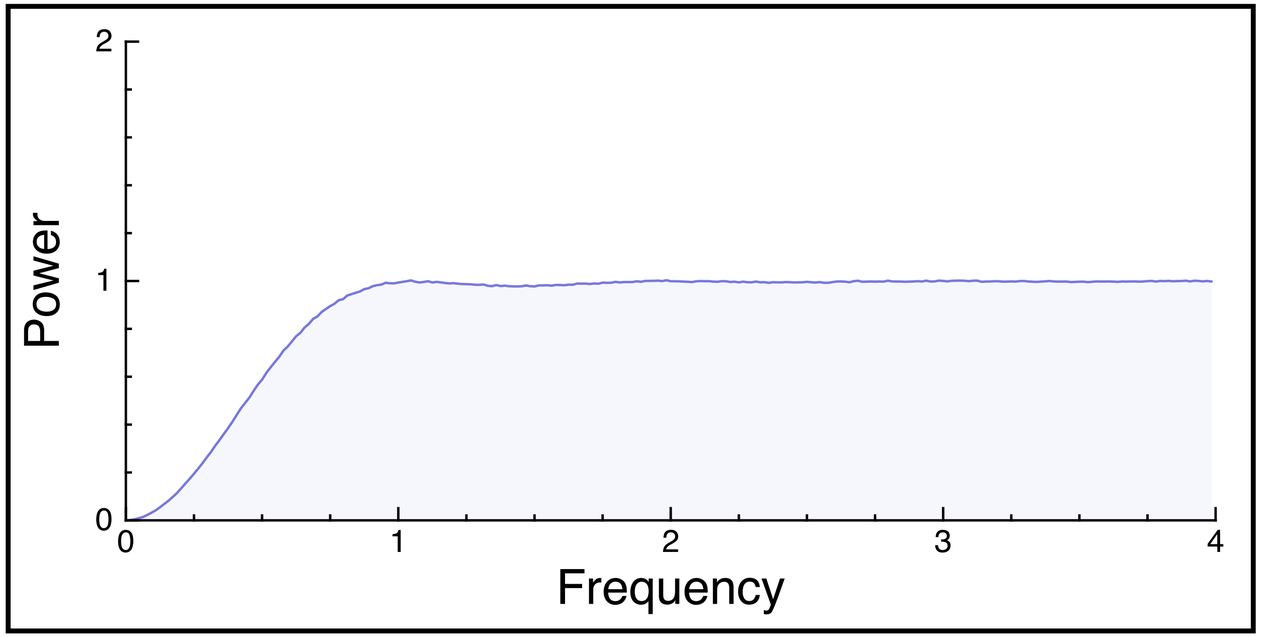
Samples



Power spectrum

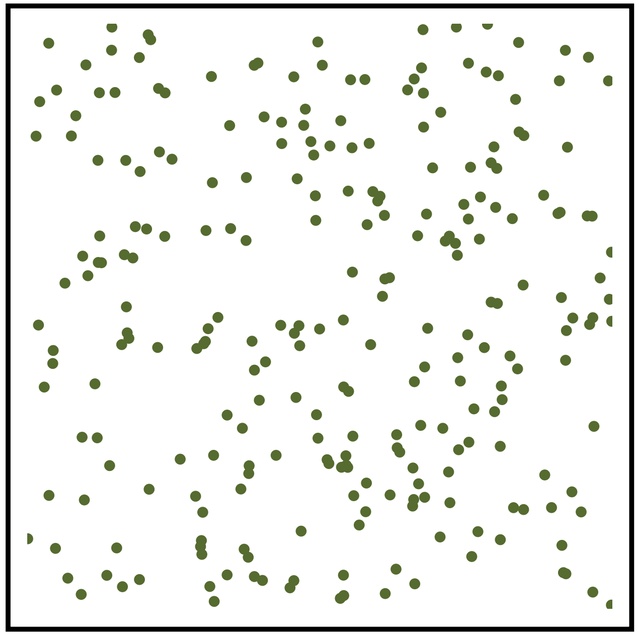


Radial mean

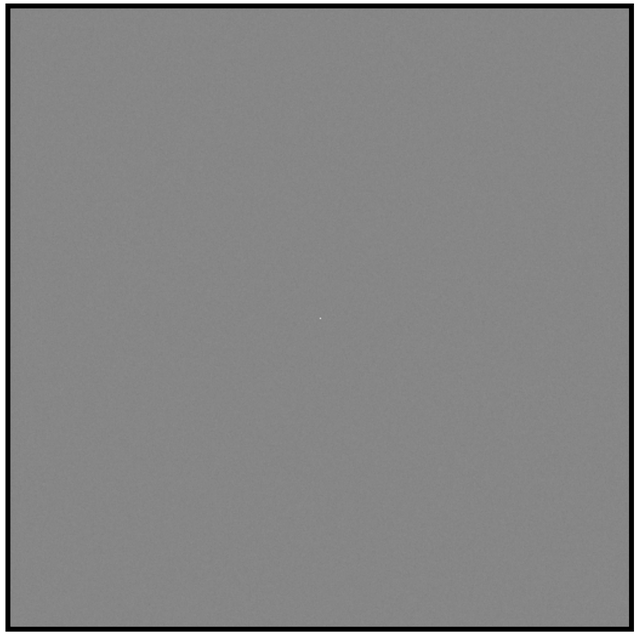


Independent Random Sampling

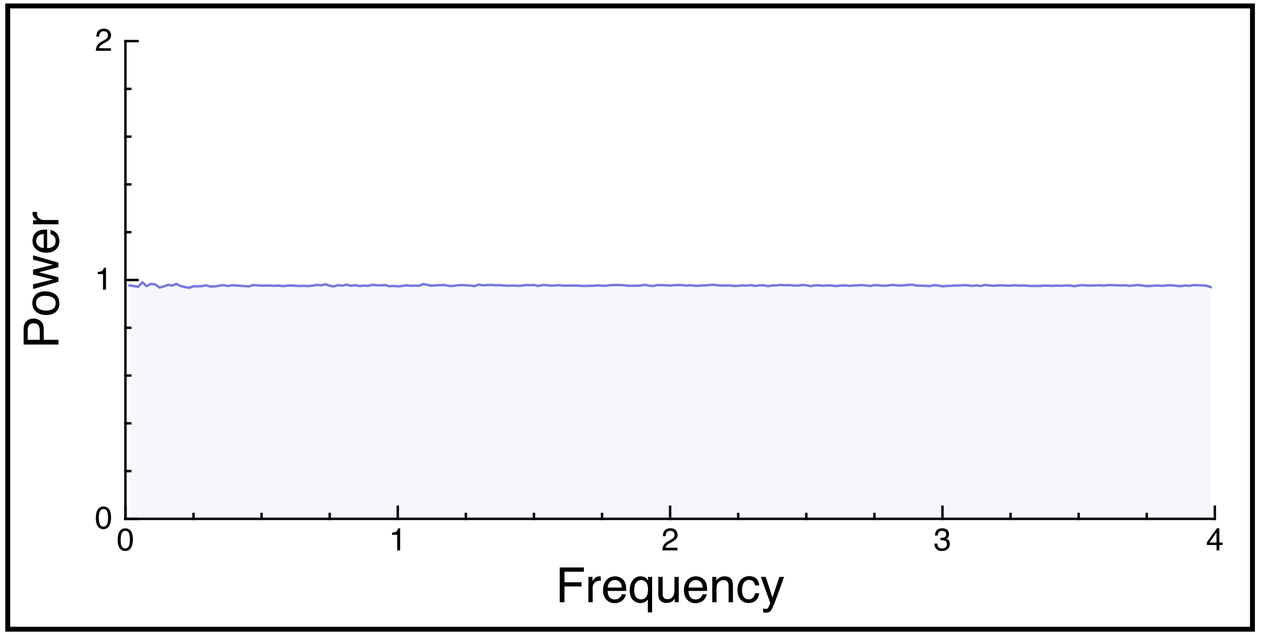
Samples



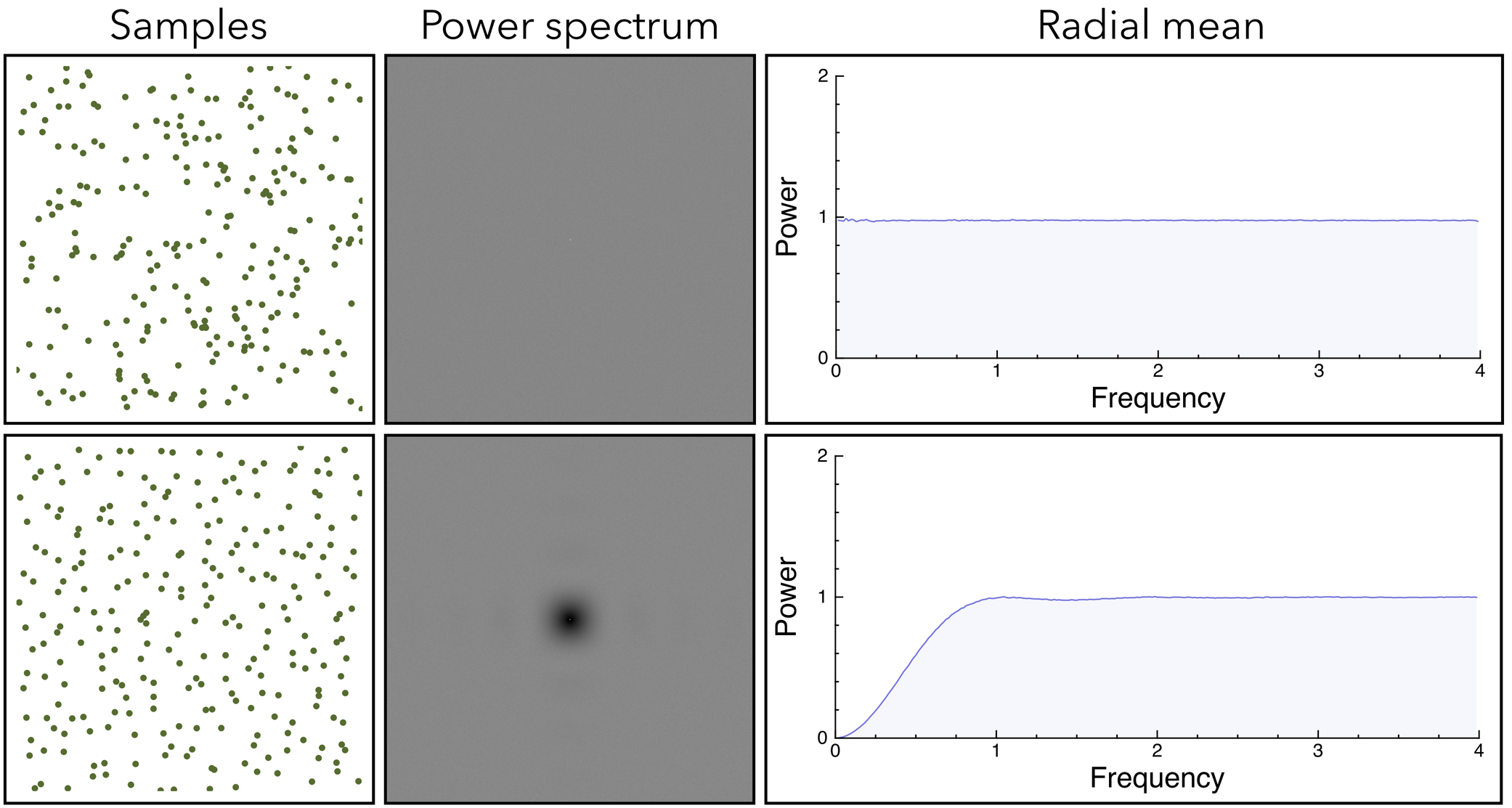
Power spectrum



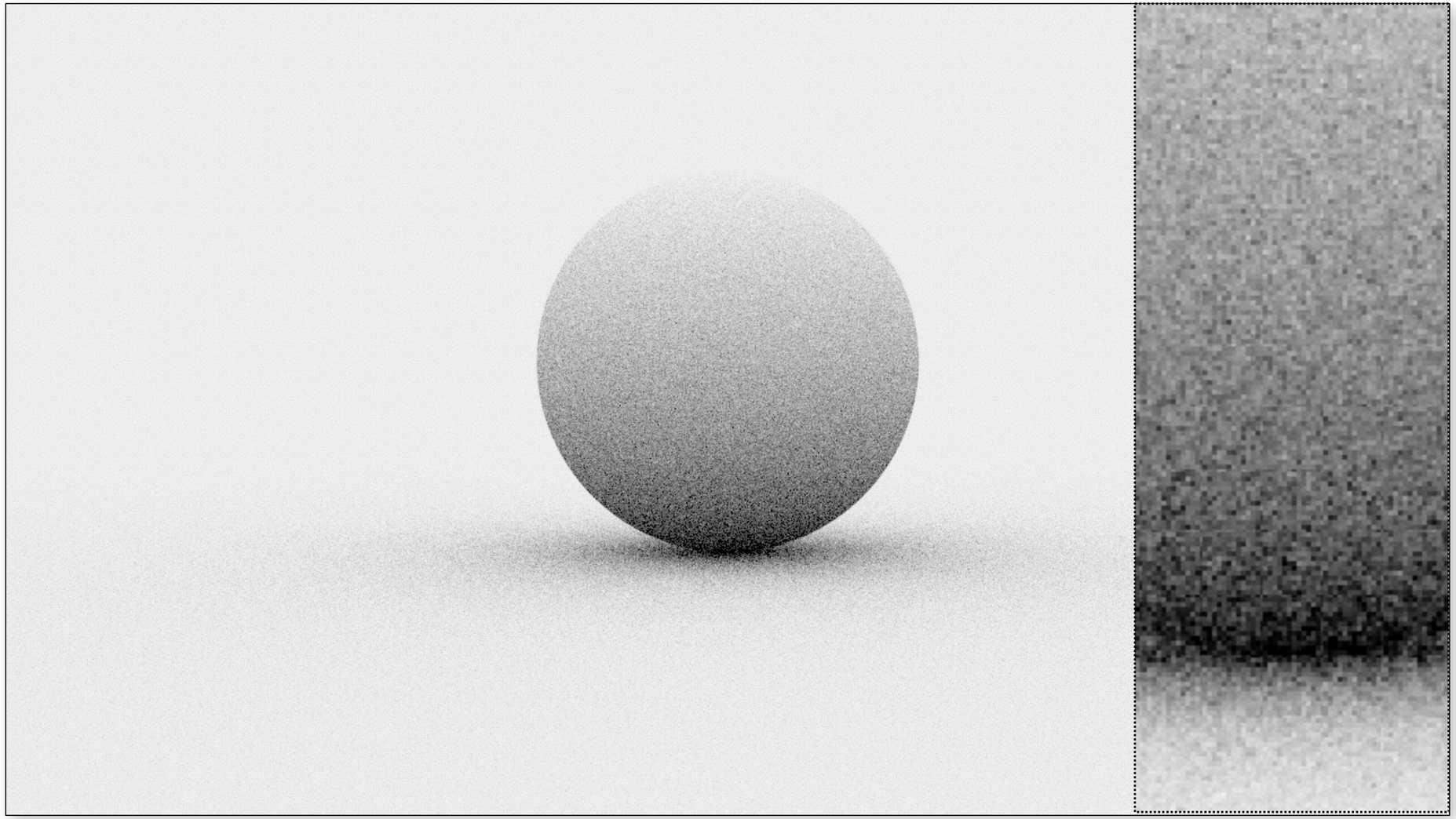
Radial mean



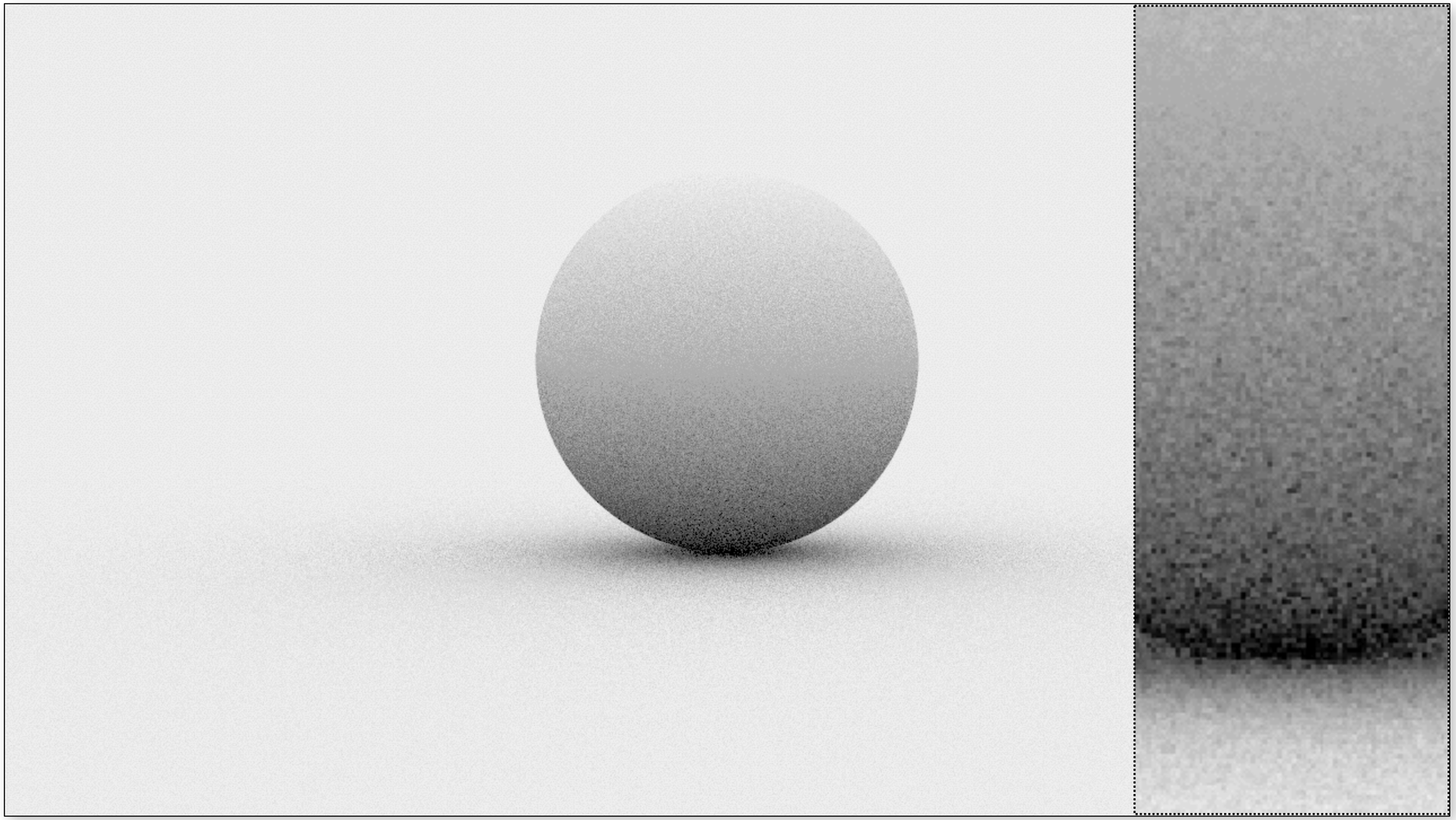
Random vs. Jittered Sampling



Monte Carlo (16 random samples)



Monte Carlo (16 stratified samples)



Stratifying in Higher Dimensions

Stratification requires O(N^d) samples

- e.g. pixel (2D) + lens (2D) + time (1D) = 5D
  - splitting 2 times in 5D = 2^5 = 32 samples
  - splitting 3 times in 5D = 3^5 = 243 samples!

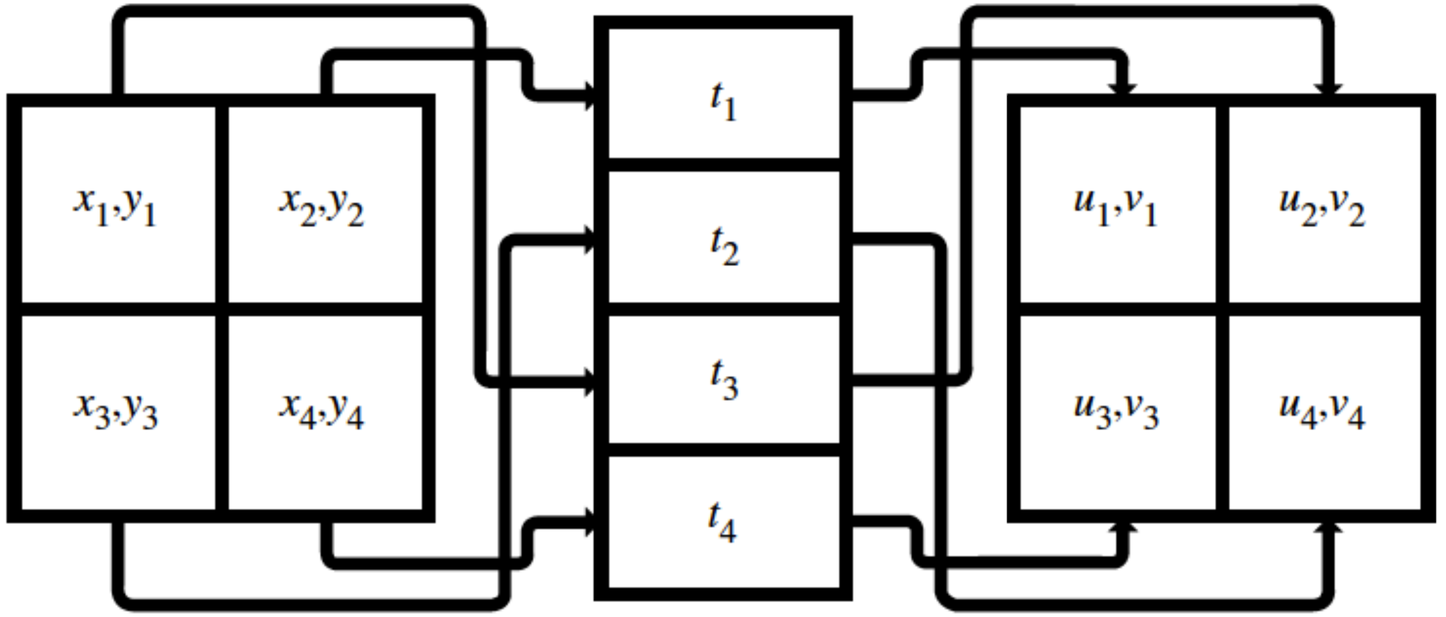
Inconvenient for large d

- cannot select sample count with fine granularity

Uncorrelated Jitter [Cook et al. 84]

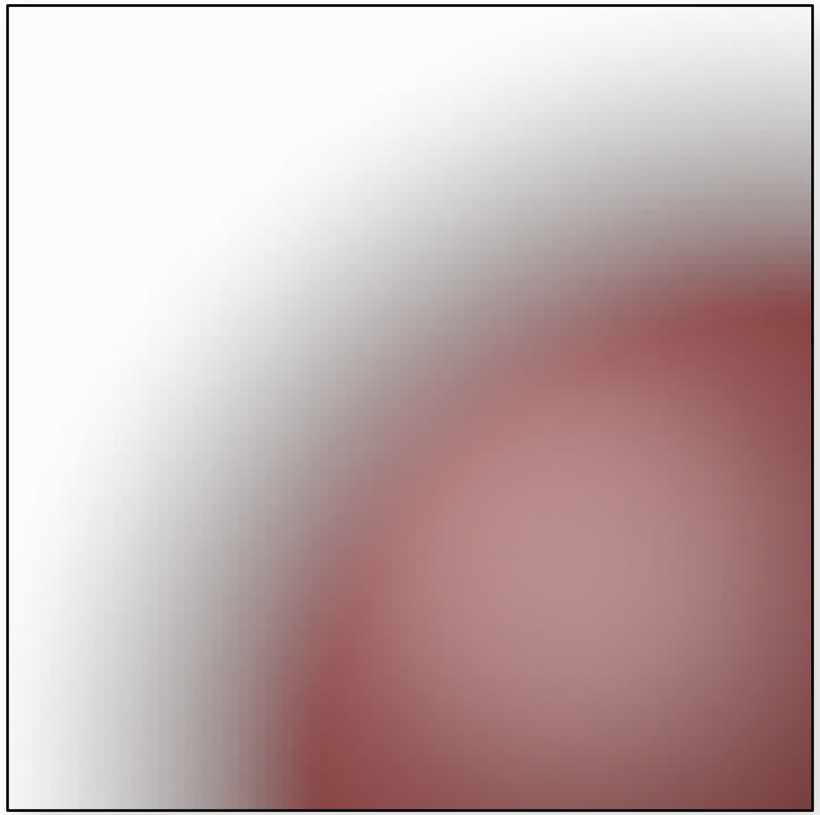
Compute stratified samples in sub-dimensions

- 2D jittered (x,y) for pixel
- 2D jittered (u,v) for lens
- 1D jittered (t) for time
- combine dimensions in random order

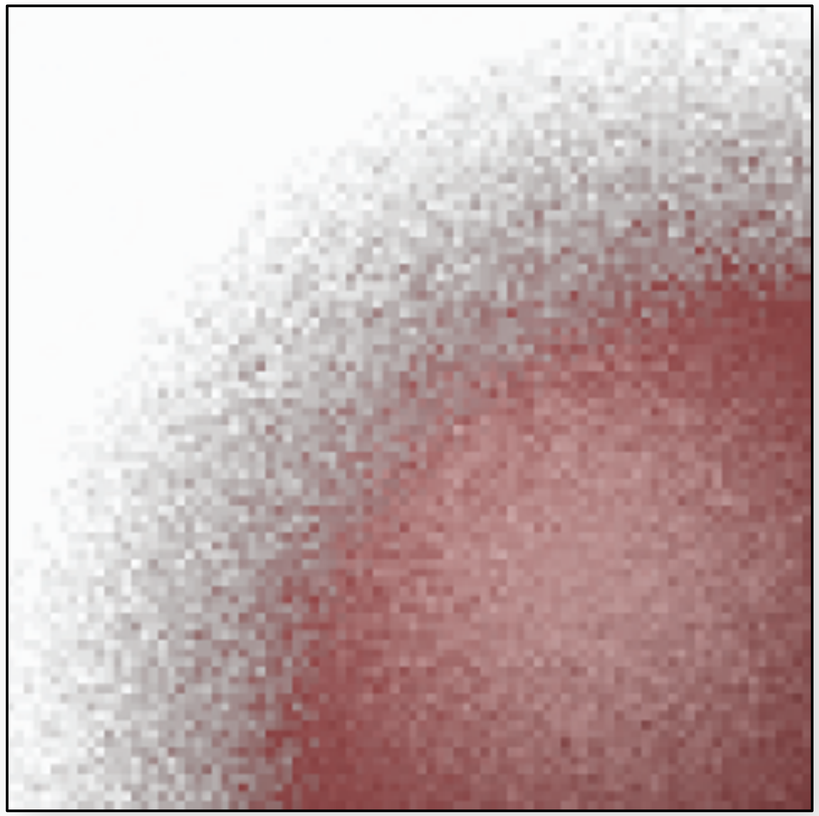


Depth of Field (4D)

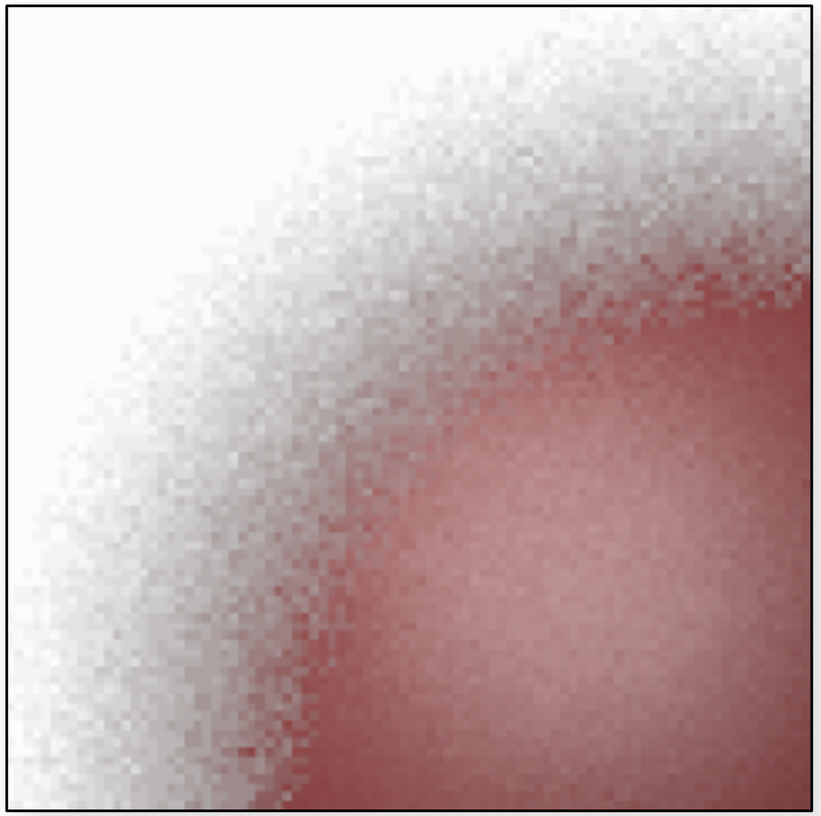
Reference



Random Sampling



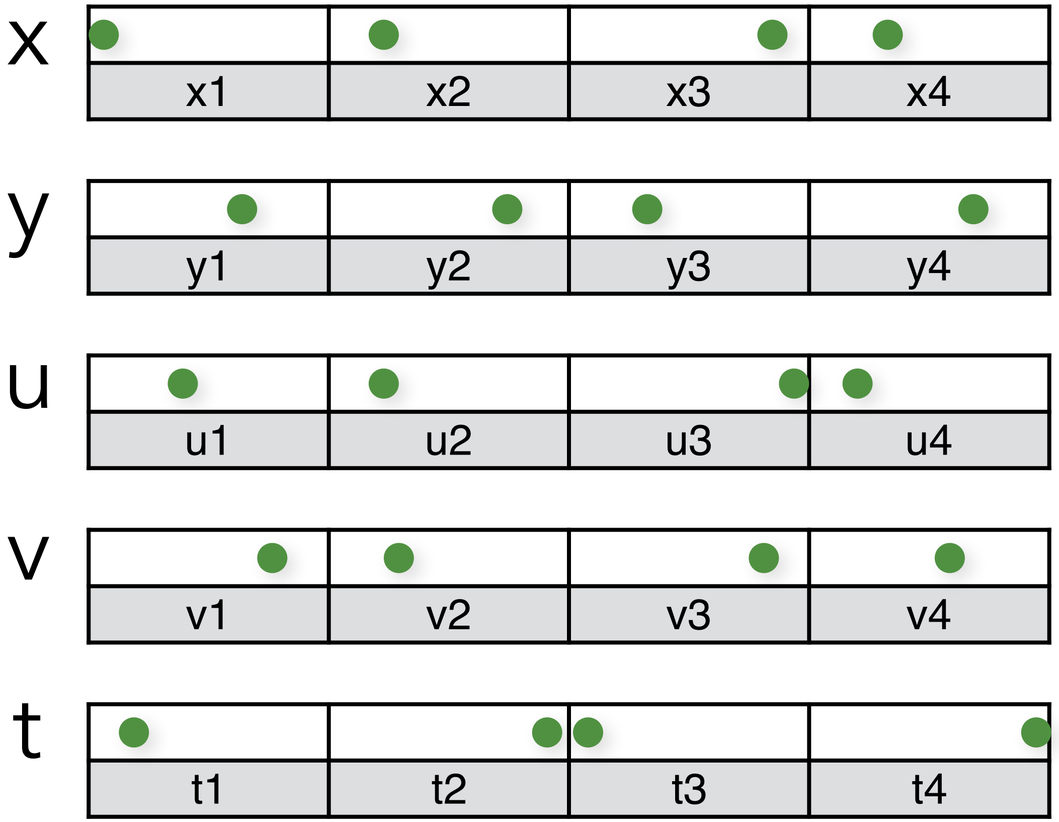
Uncorrelated Jitter



Uncorrelated Jitter → Latin Hypercube

Stratify samples in each dimension separately

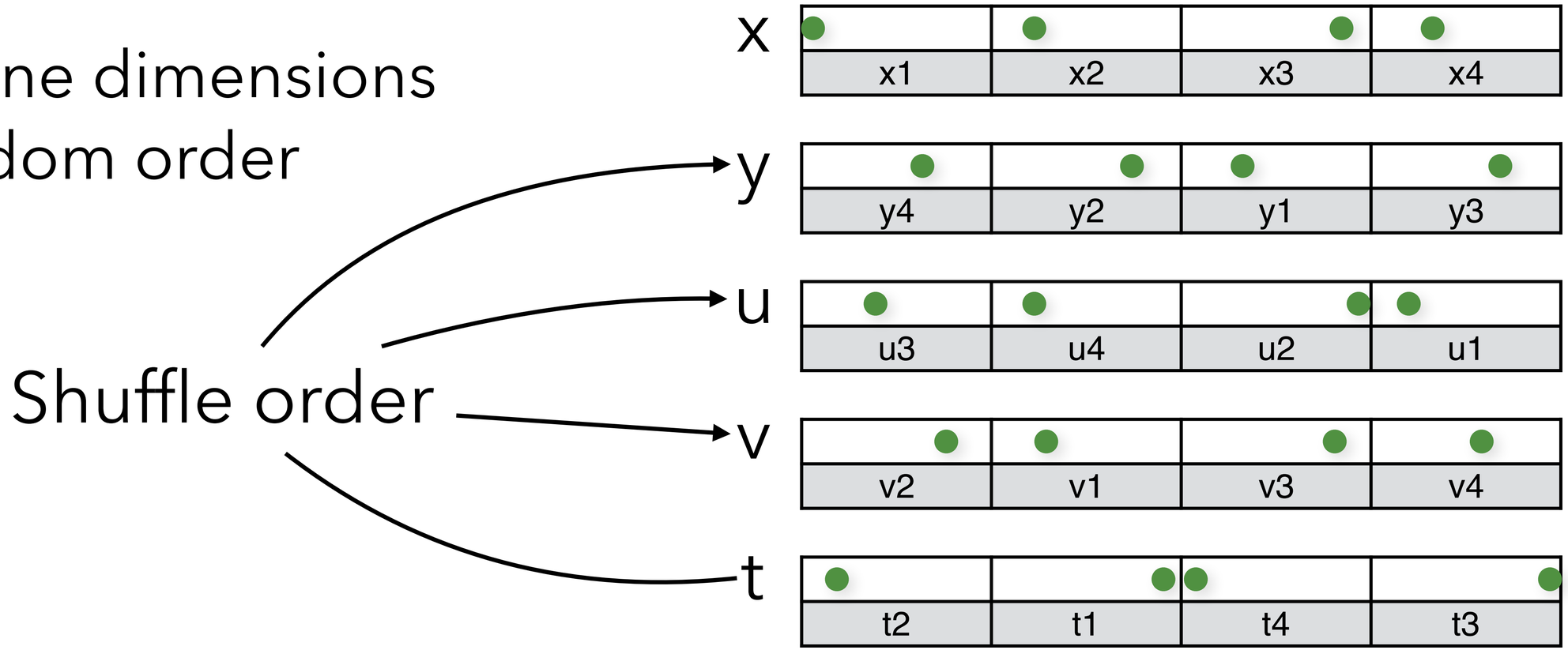
- for 5D: 5 separate 1D jittered point sets
- combine dimensions in random order



Uncorrelated Jitter → Latin Hypercube

Stratify samples in each dimension separately

- for 5D: 5 separate 1D jittered point sets
- combine dimensions in random order



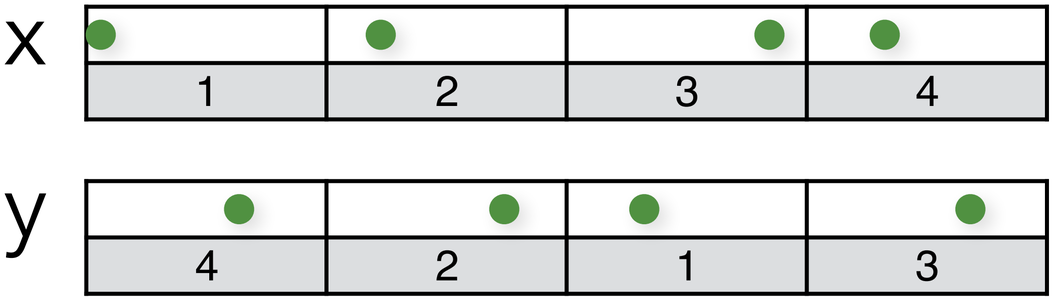
Latin Hypercube Sampling

```
// initialize the diagonal
for (uint d = 0; d < numDimensions; d++)
      for (uint i = 0; i < numSamples; i++)
            samples(d,i) = (i + randf())/numSamples;

// shuffle each dimension independently
for (uint d = 0; d < numDimensions; d++)
      for (uint i = numSamples-1; i >= 1; i--)
            swap(samples(d,i), samples(d, randi(0,i)));
```

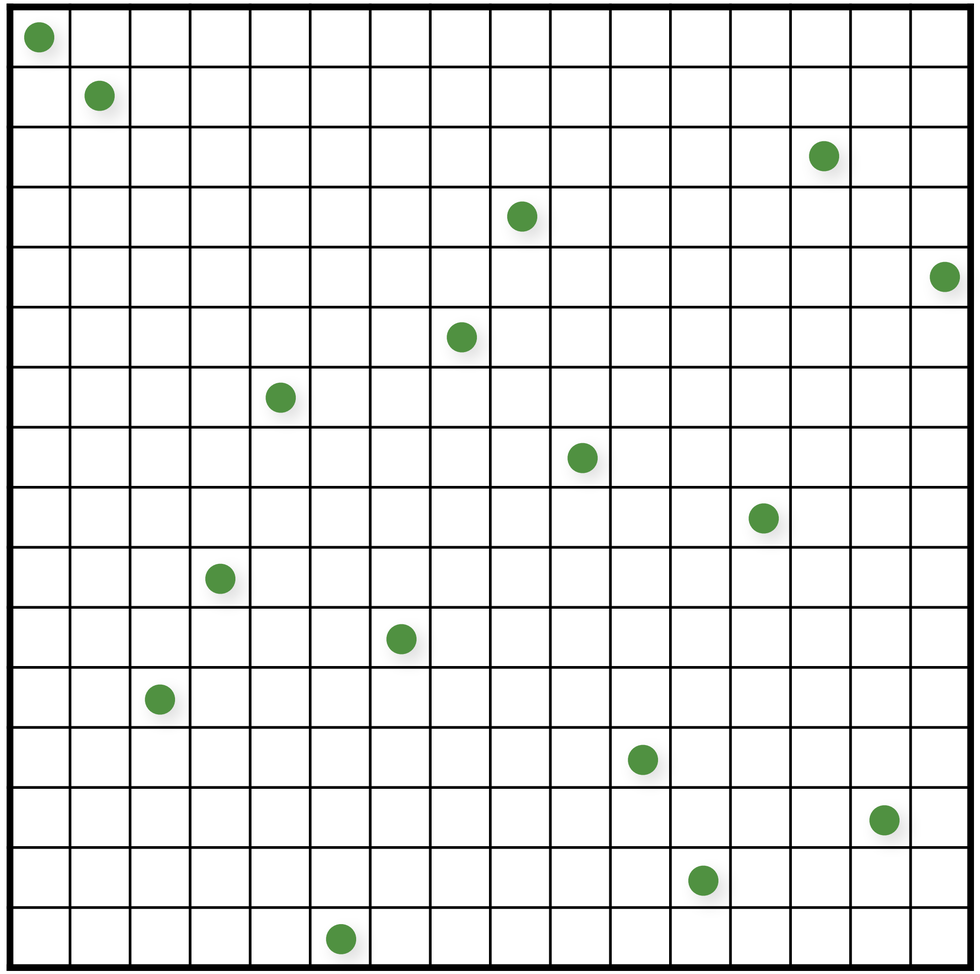
N-Rooks = 2D Latin Hypercube

Stratify samples in each dimension separately

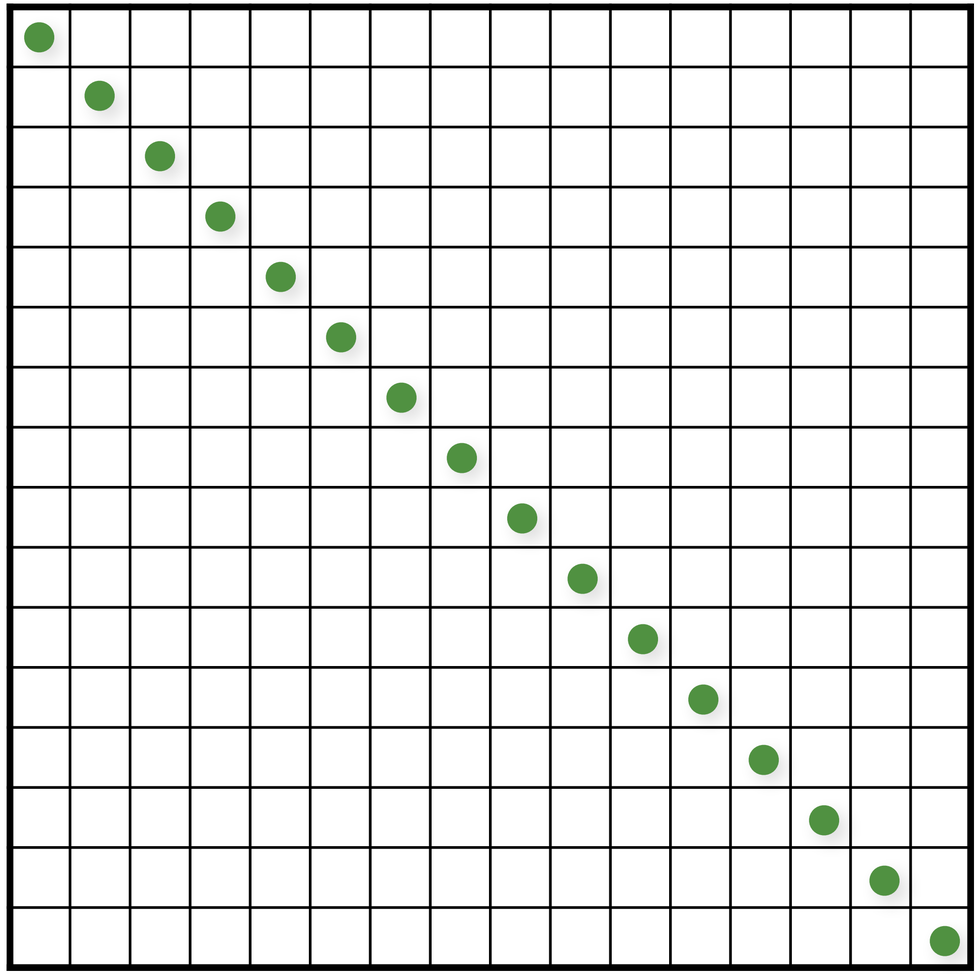
- for 2D: 2 separate 1D jittered point sets
- combine dimensions in random order



Latin Hypercube (N-Rooks) Sampling

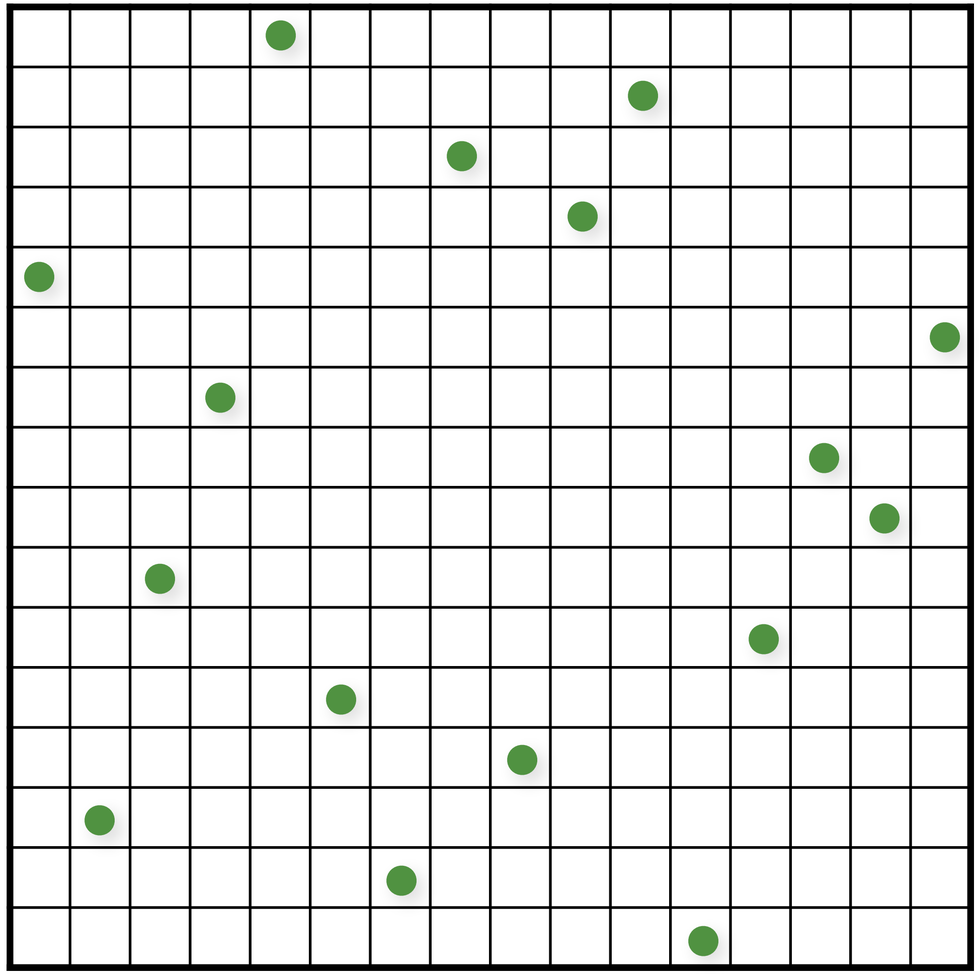


Latin Hypercube (N-Rooks) Sampling



Shuffle rows

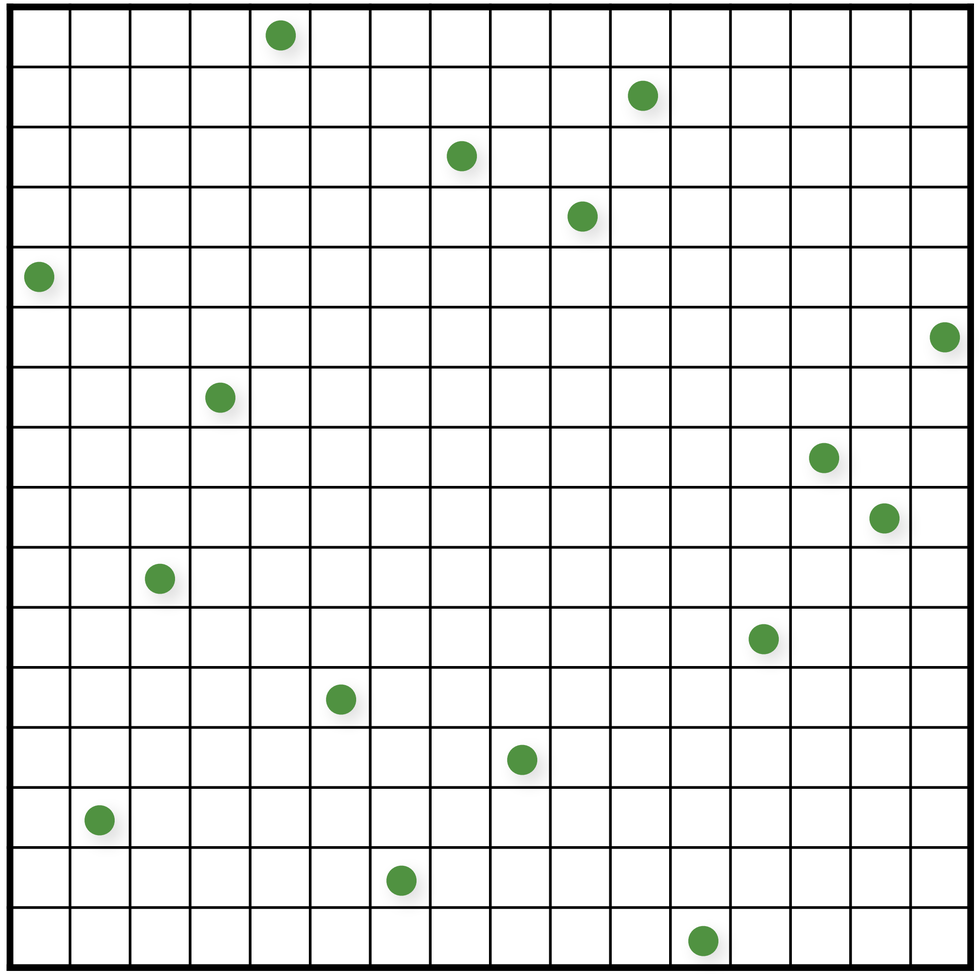
Latin Hypercube (N-Rooks) Sampling



Shuffle rows

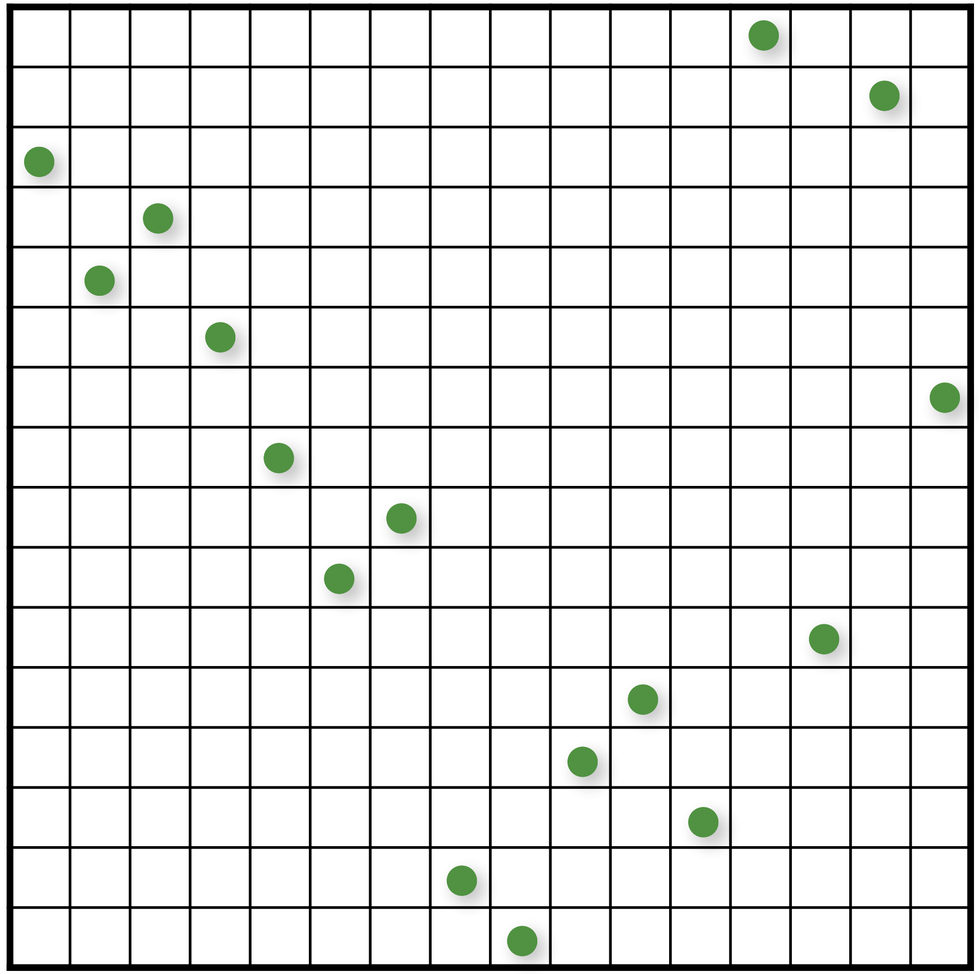
Shuffle columns

Latin Hypercube (N-Rooks) Sampling

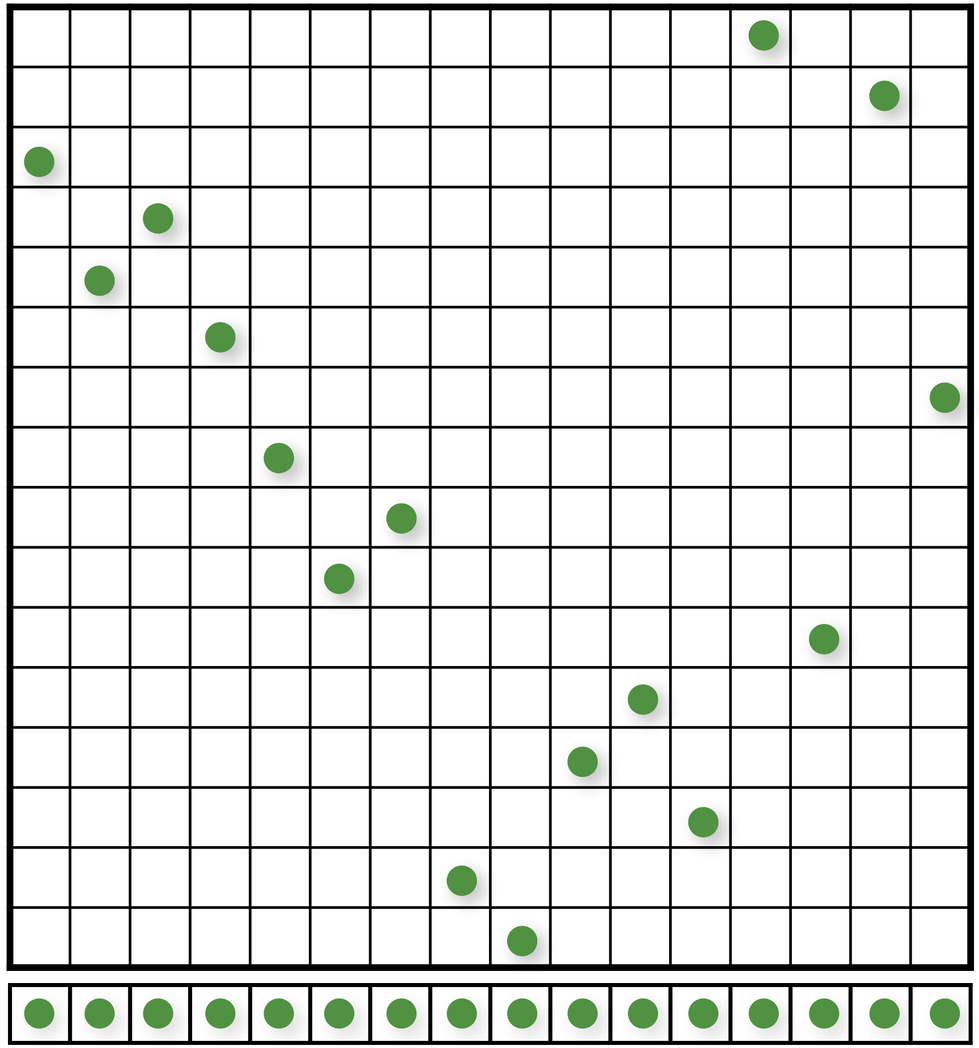


Shuffle columns

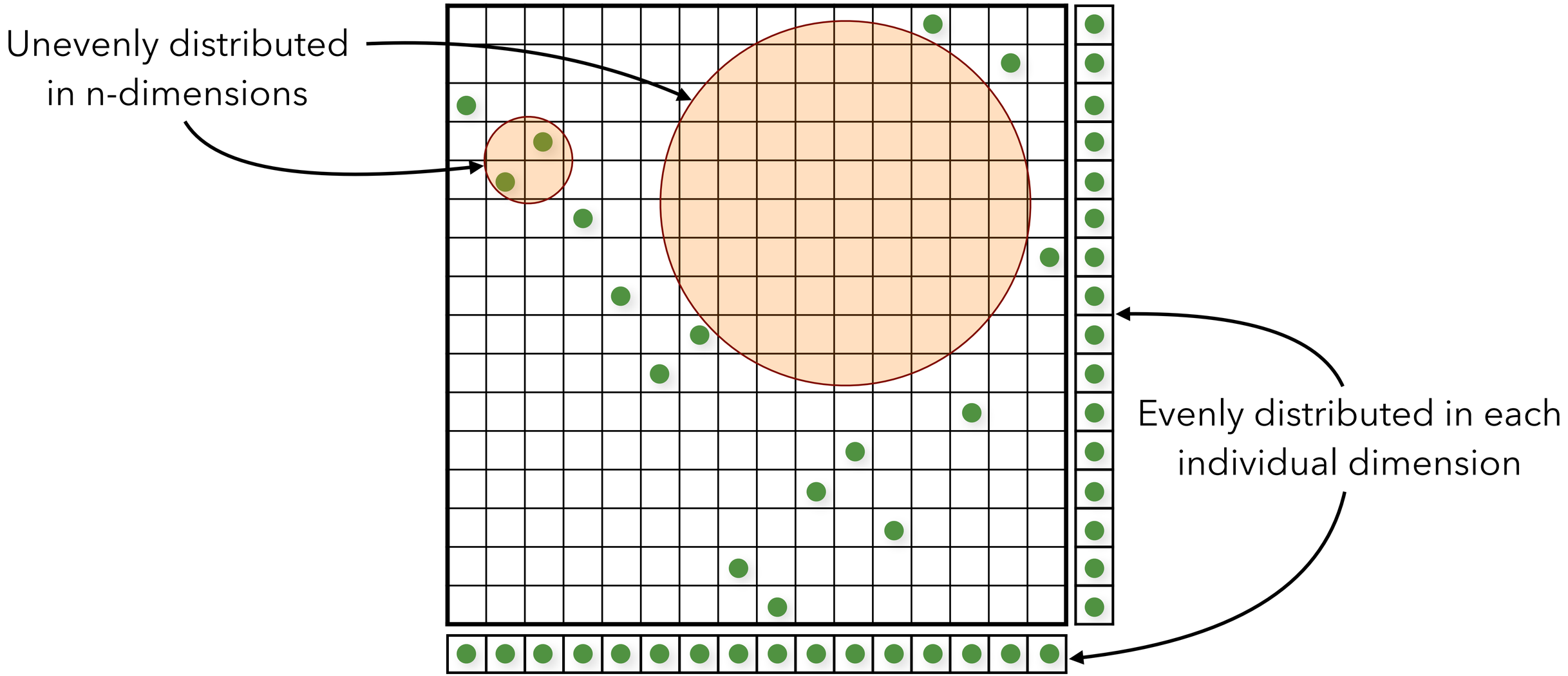
Latin Hypercube (N-Rooks) Sampling



Latin Hypercube (N-Rooks) Sampling

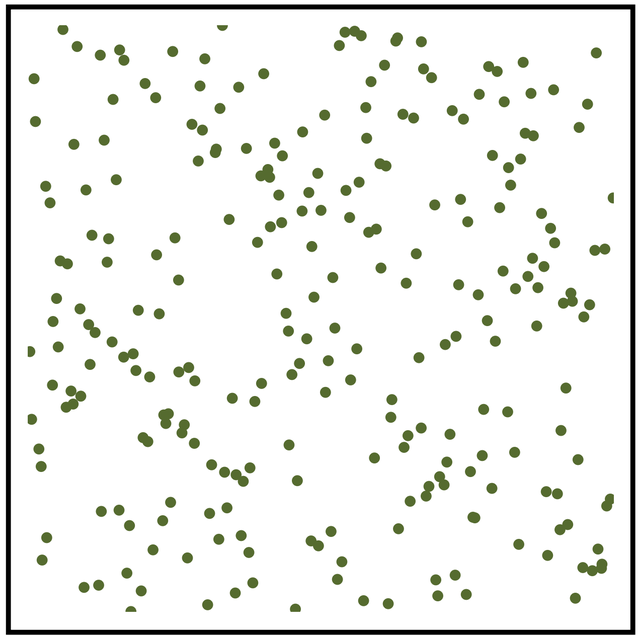


Latin Hypercube (N-Rooks) Sampling

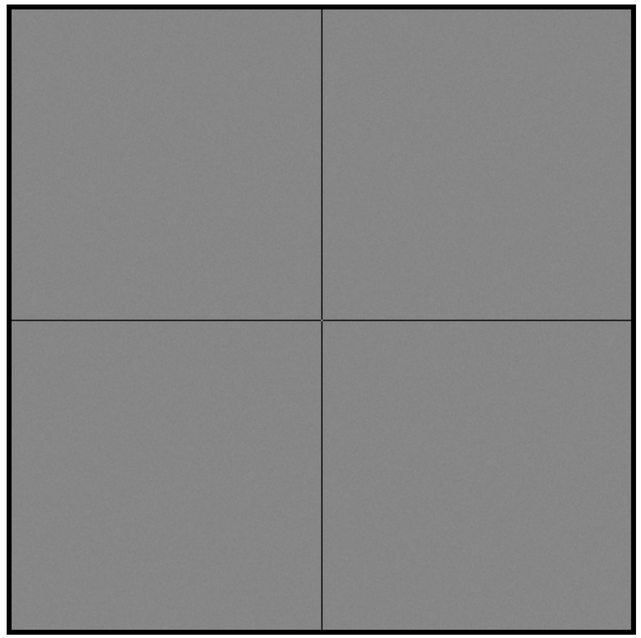


N-Rooks Sampling

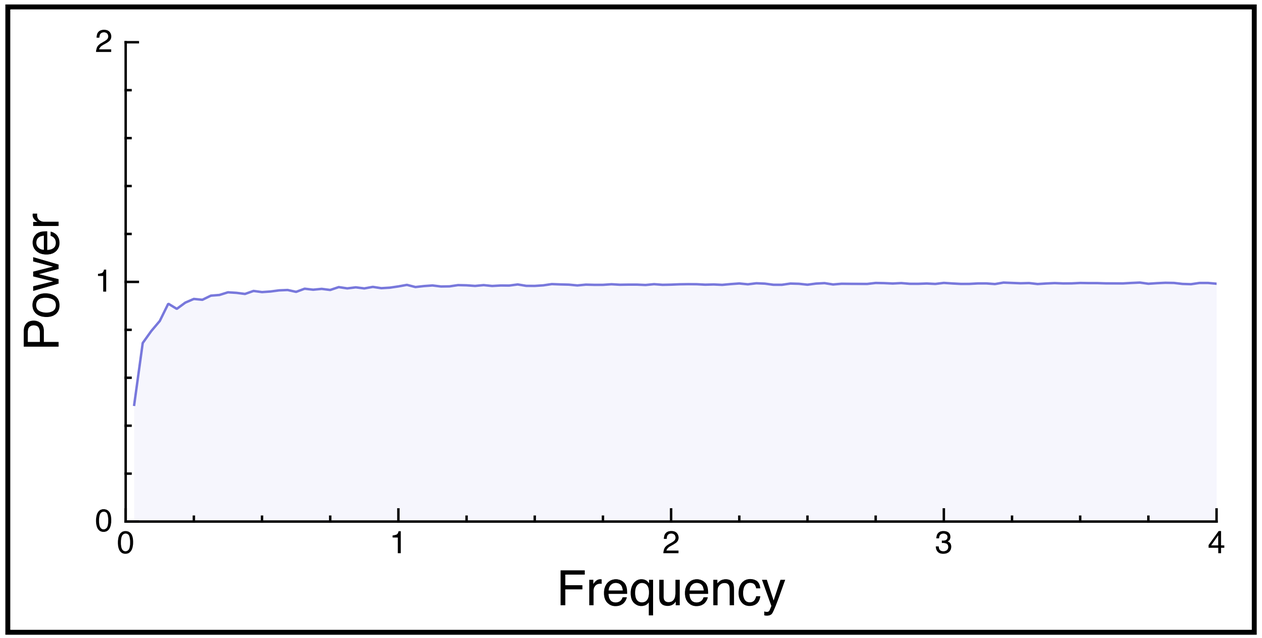
Samples



Power spectrum



Radial mean

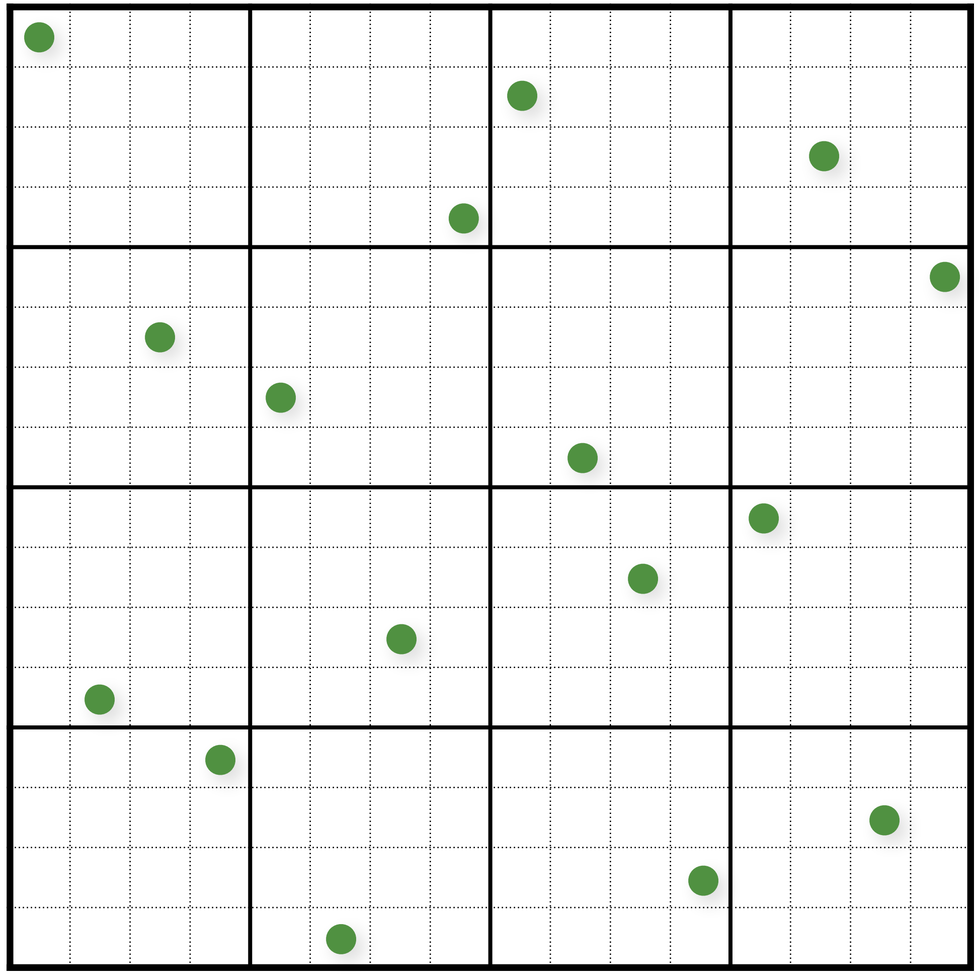


Multi-Jittered Sampling

Kenneth Chiu, Peter Shirley, and Changyaw Wang. "Multi-jittered sampling." In *Graphics Gems IV*, pp. 370–374. Academic Press, May 1994.

- combine N-Rooks and Jittered stratification constraints

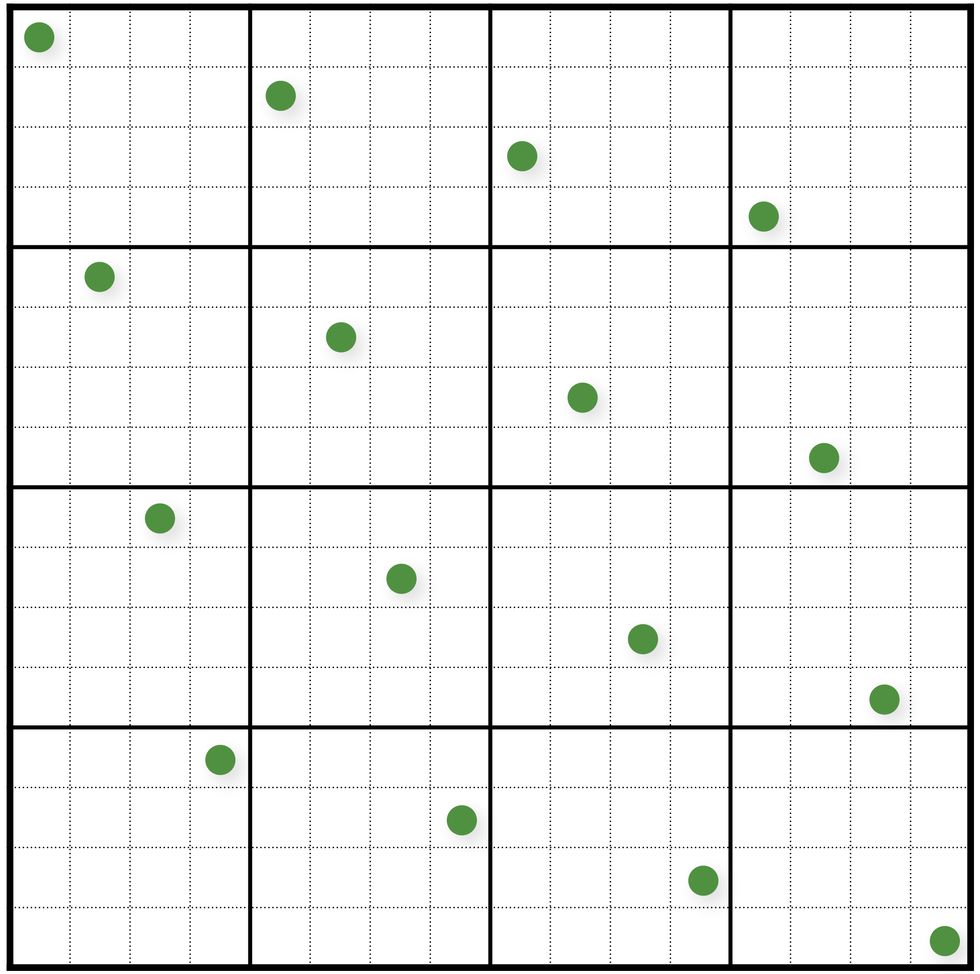
Multi-Jittered Sampling



Multi-Jittered Sampling

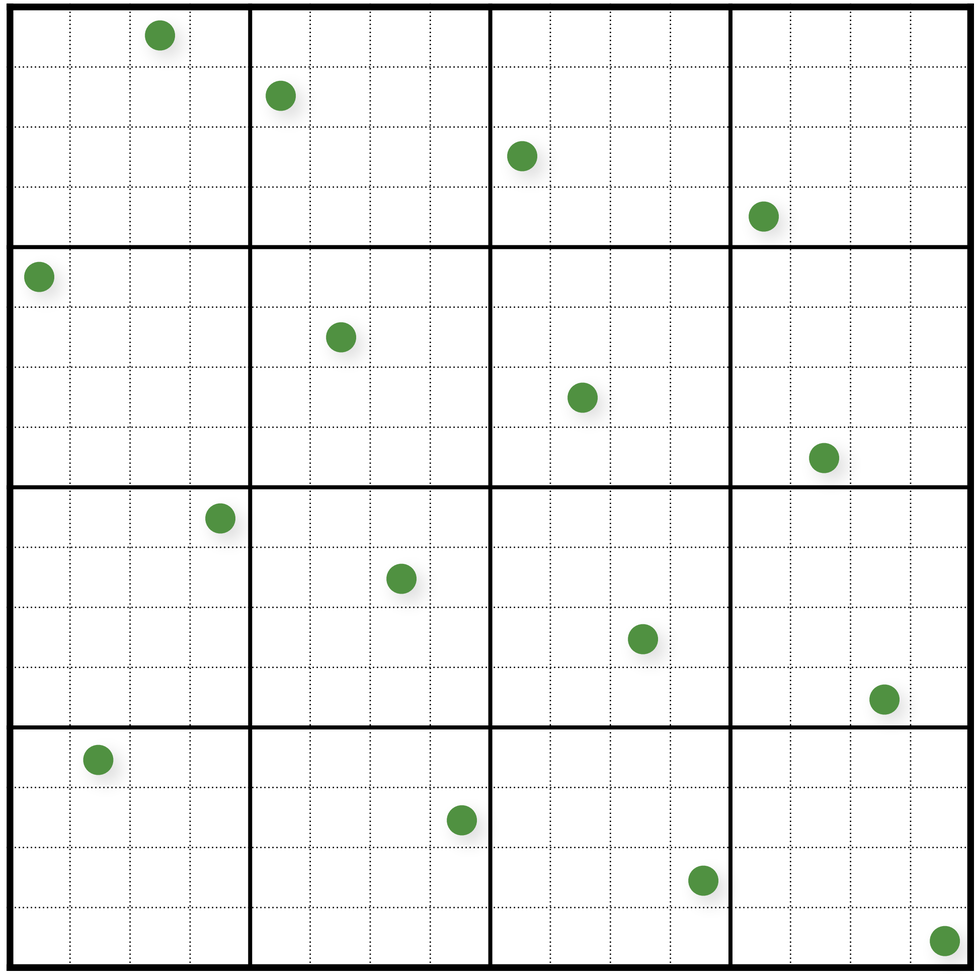
```
// initialize
float cellSize = 1.0 / (resX*resY);
for (uint i = 0; i < resX; i++)
	for (uint j = 0; j < resY; j++)
	{
		samples(i,j).x = i/resX + (j+randf()) / (resX*resY);
		samples(i,j).y = j/resY + (i+randf()) / (resX*resY);
	}

// shuffle x coordinates within each column of cells
for (uint i = 0; i < resX; i++)
	for (uint j = resY-1; j >= 1; j--)
		swap(samples(i, j).x, samples(i, randi(0, j)).x);

// shuffle y coordinates within each row of cells
for (unsigned j = 0; j < resY; j++)
	for (unsigned i = resX-1; i >= 1; i--)
		swap(samples(i, j).y, samples(randi(0, i), j).y);
```

Multi-Jittered Sampling



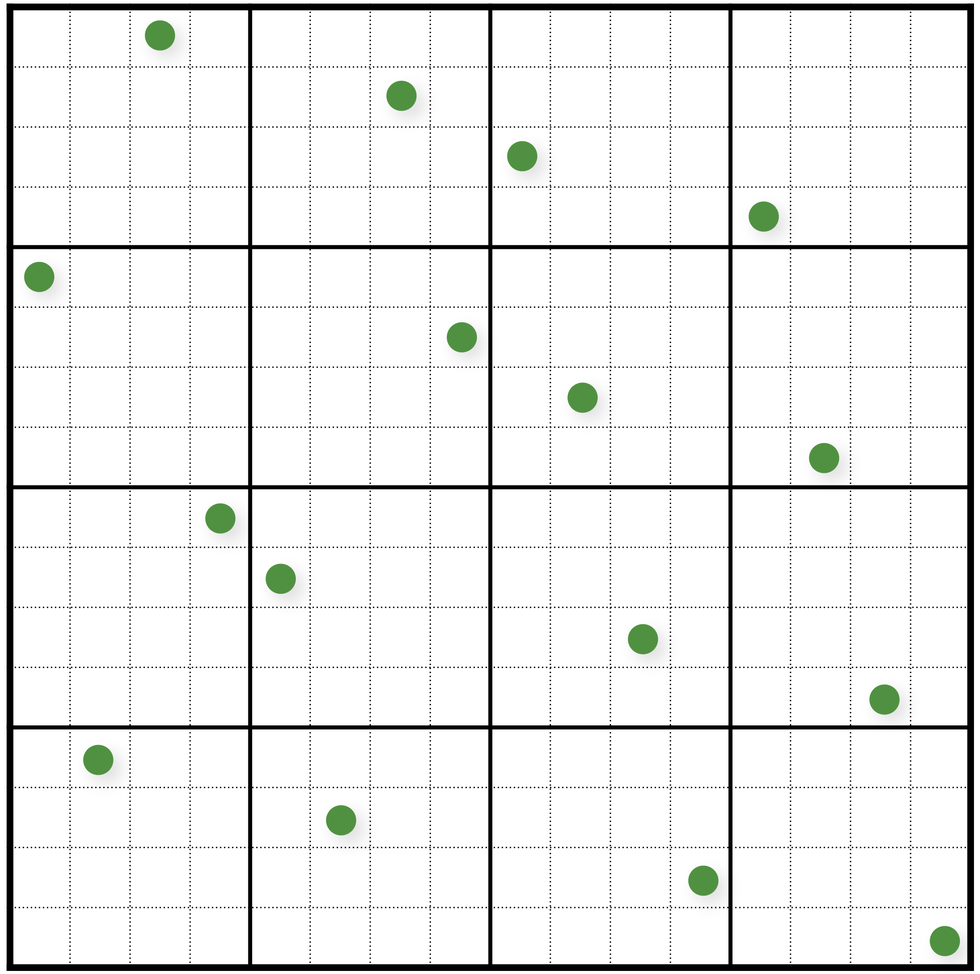
Shuffle x-coords

Multi-Jittered Sampling



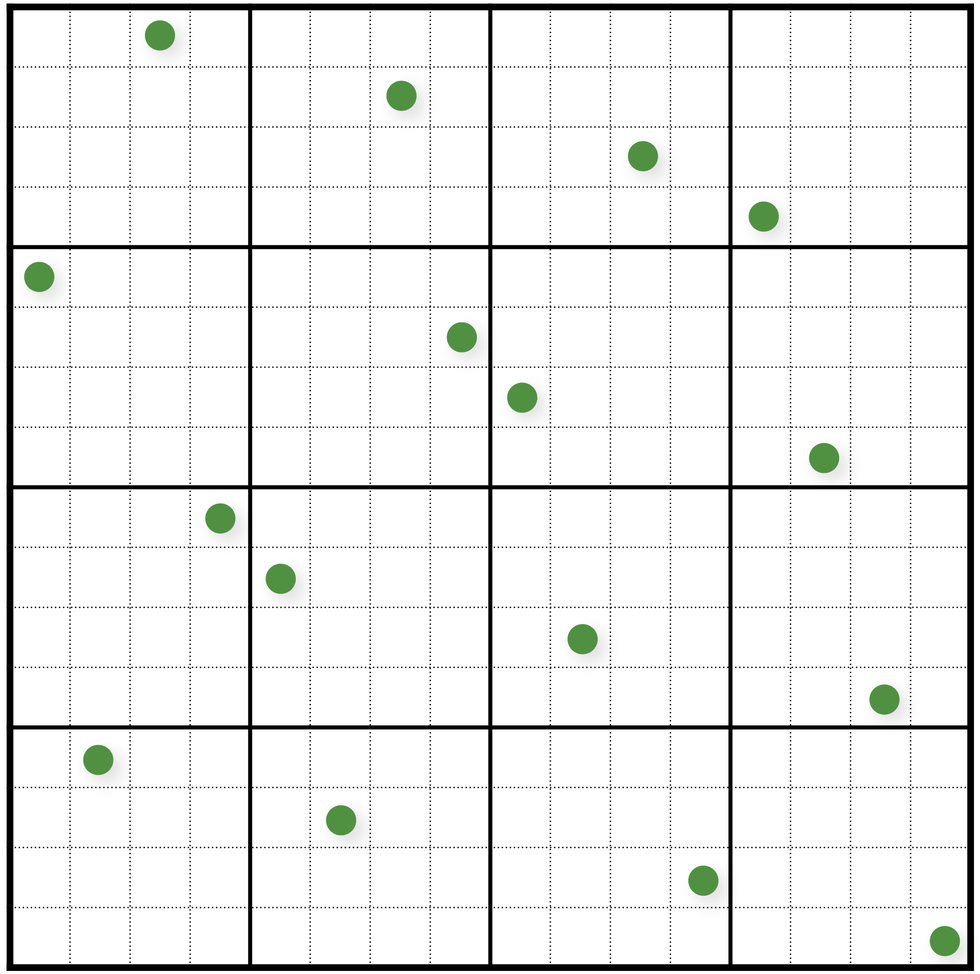
Shuffle x-coords

Multi-Jittered Sampling



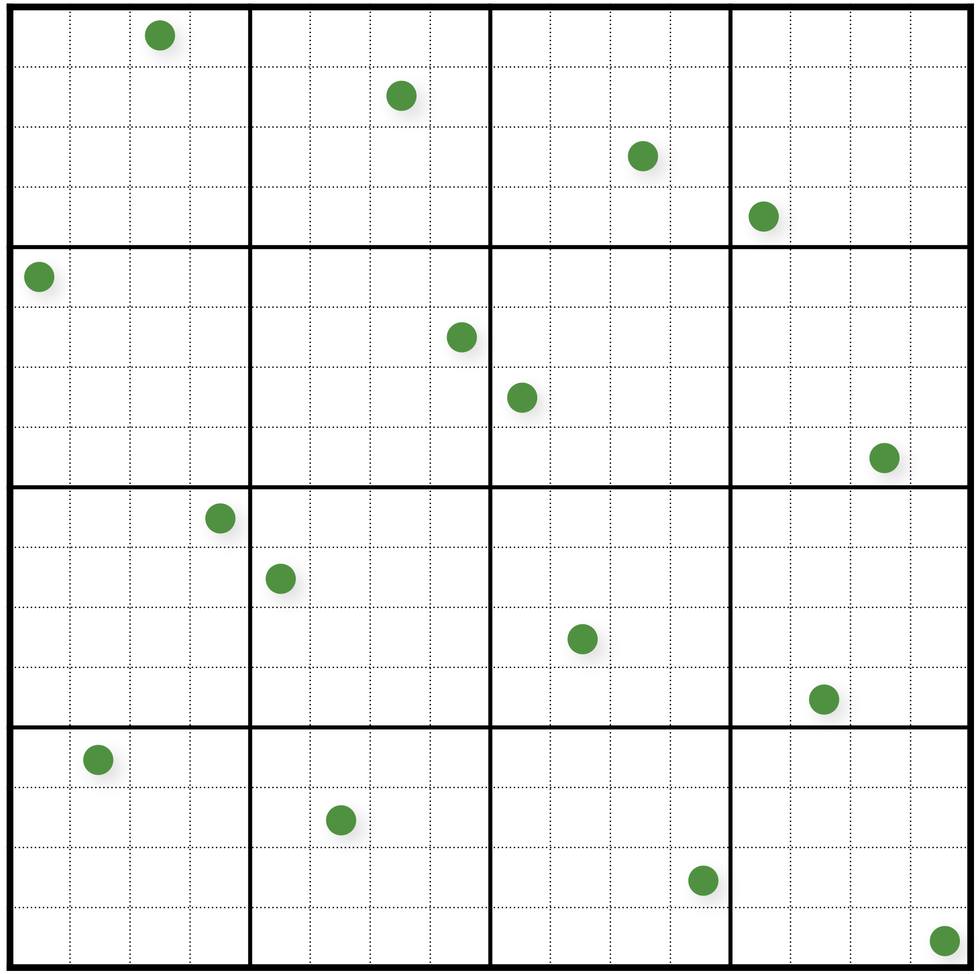
Shuffle x-coords

Multi-Jittered Sampling



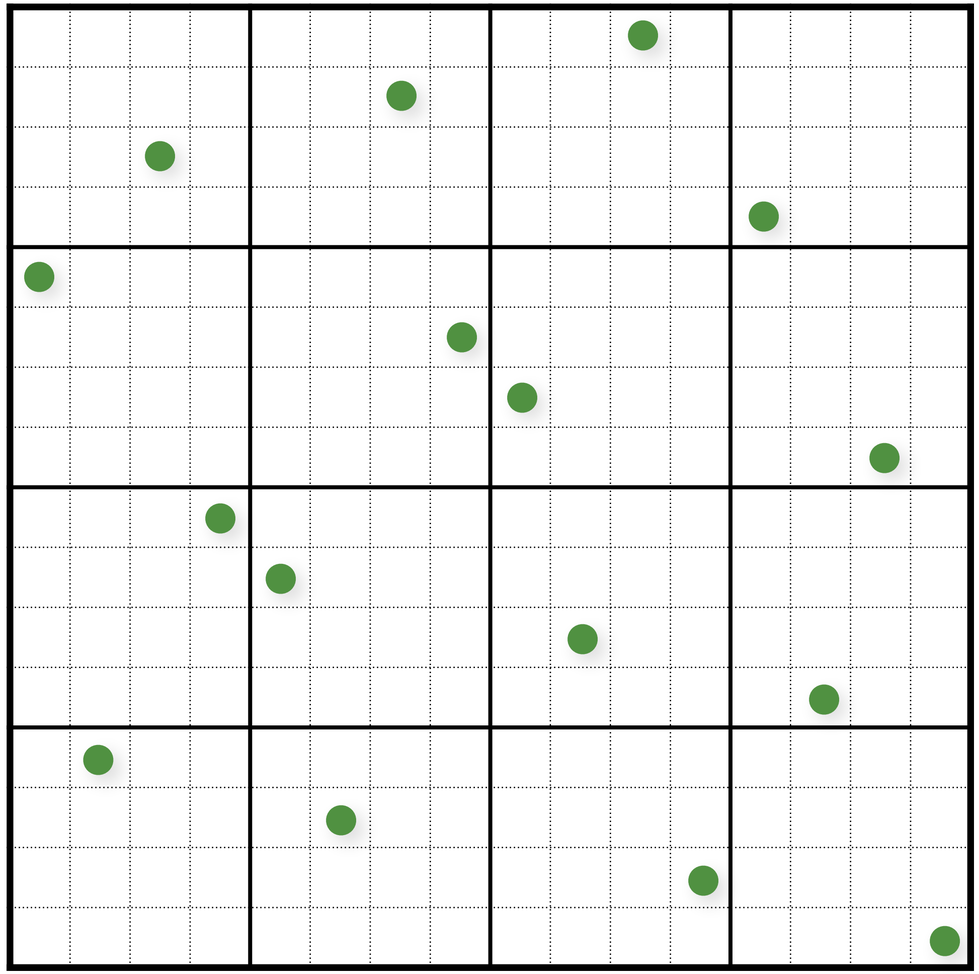
Shuffle x-coords

Multi-Jittered Sampling



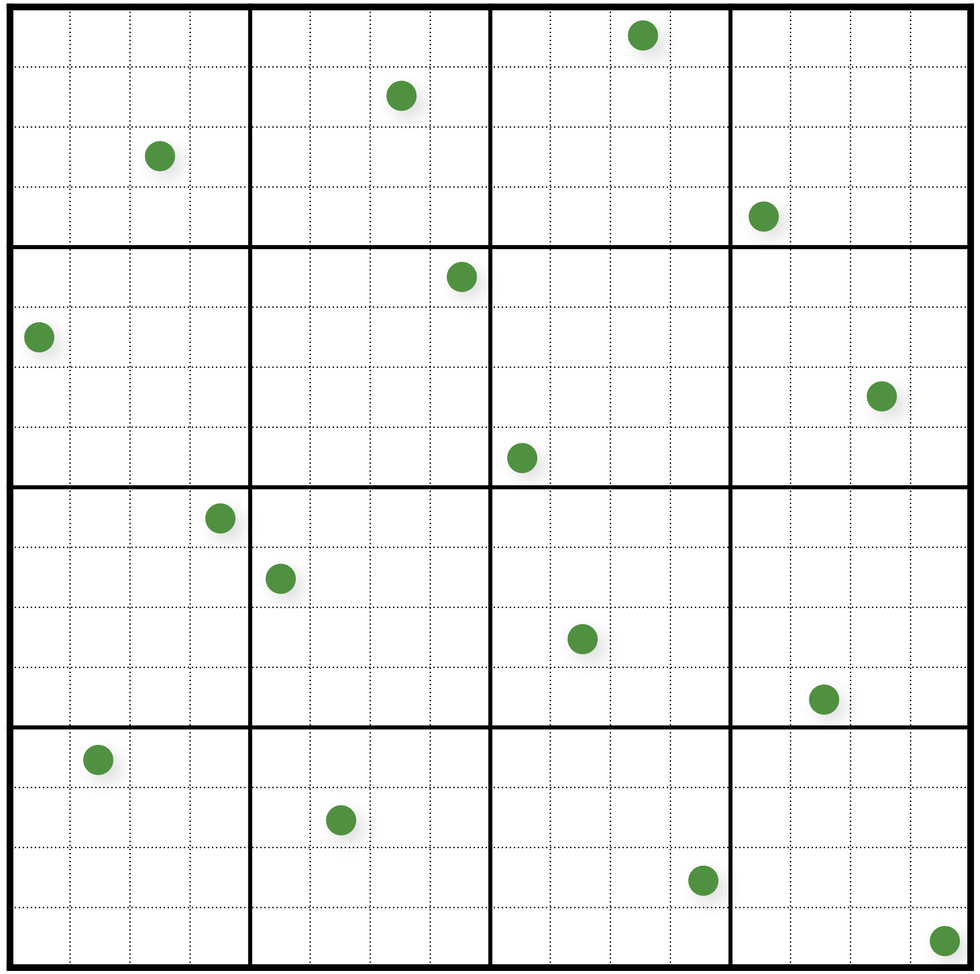
Shuffle x-coords

Multi-Jittered Sampling



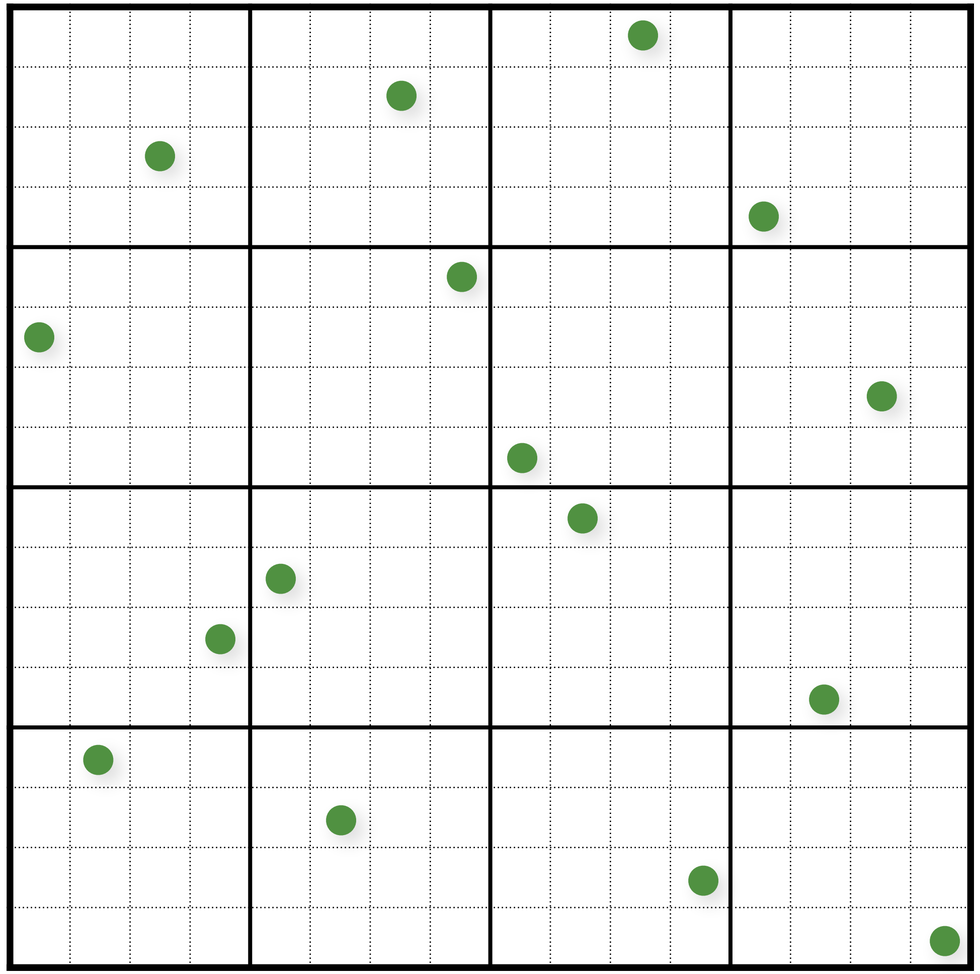
Shuffle y-coords

Multi-Jittered Sampling



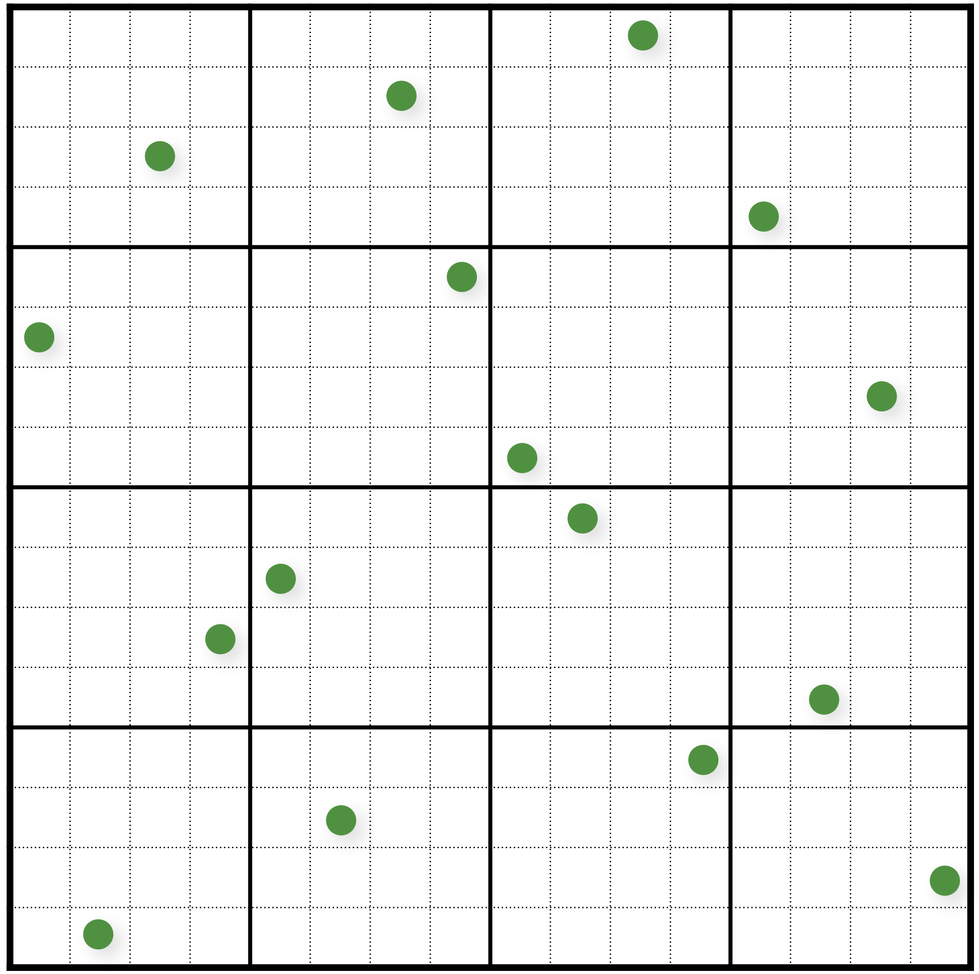
Shuffle y-coords

Multi-Jittered Sampling



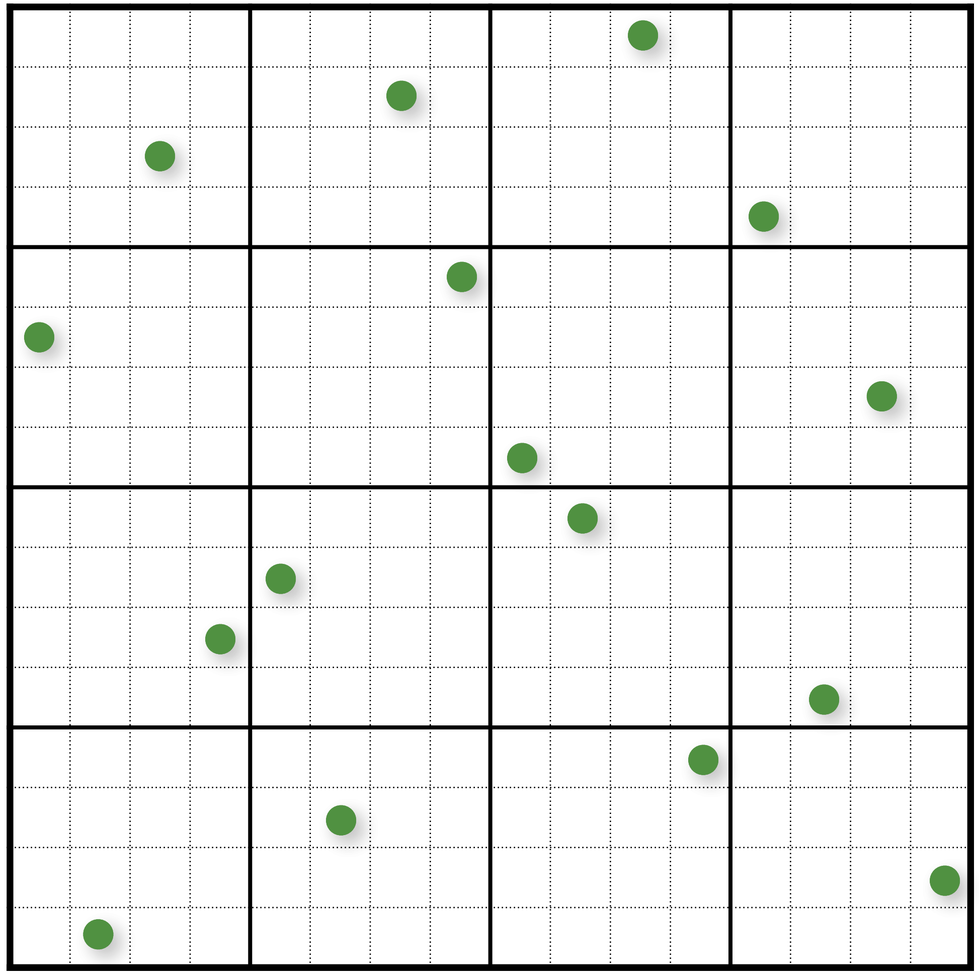
Shuffle y-coords

Multi-Jittered Sampling

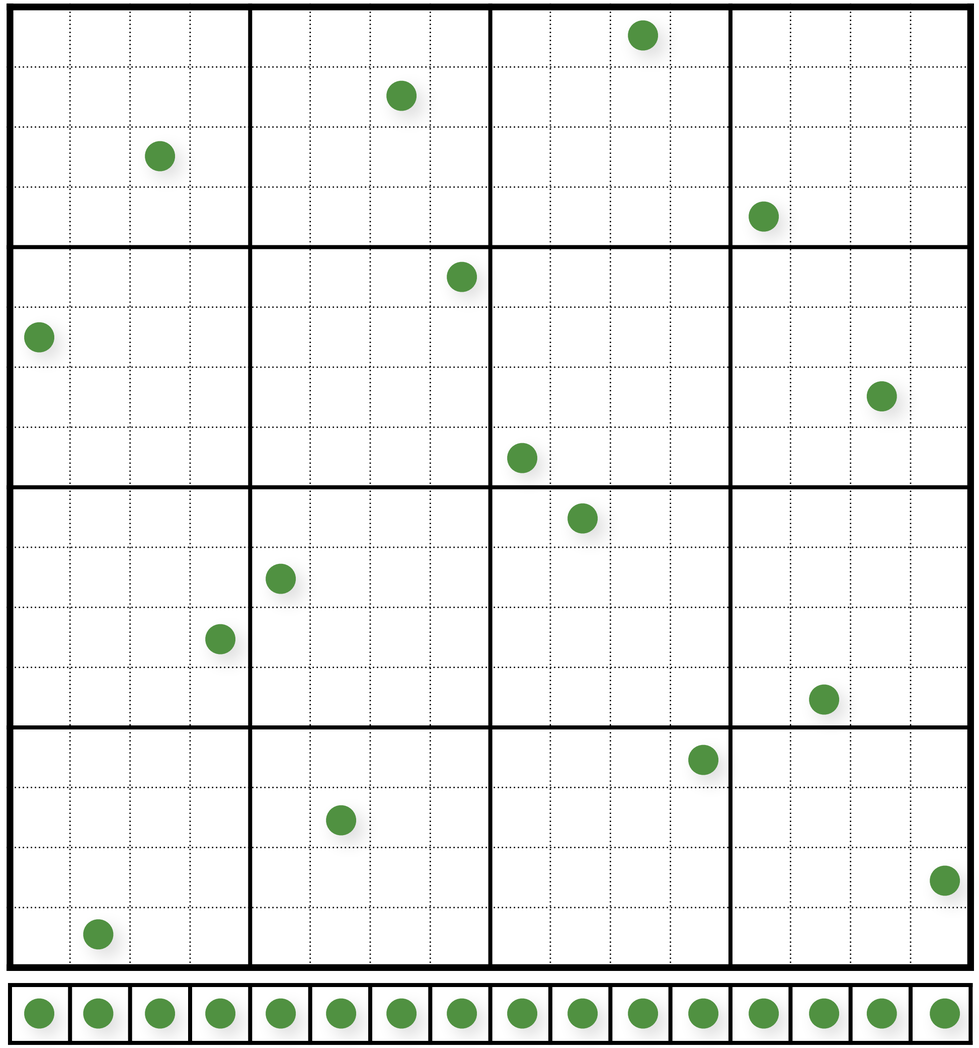


Shuffle y-coords

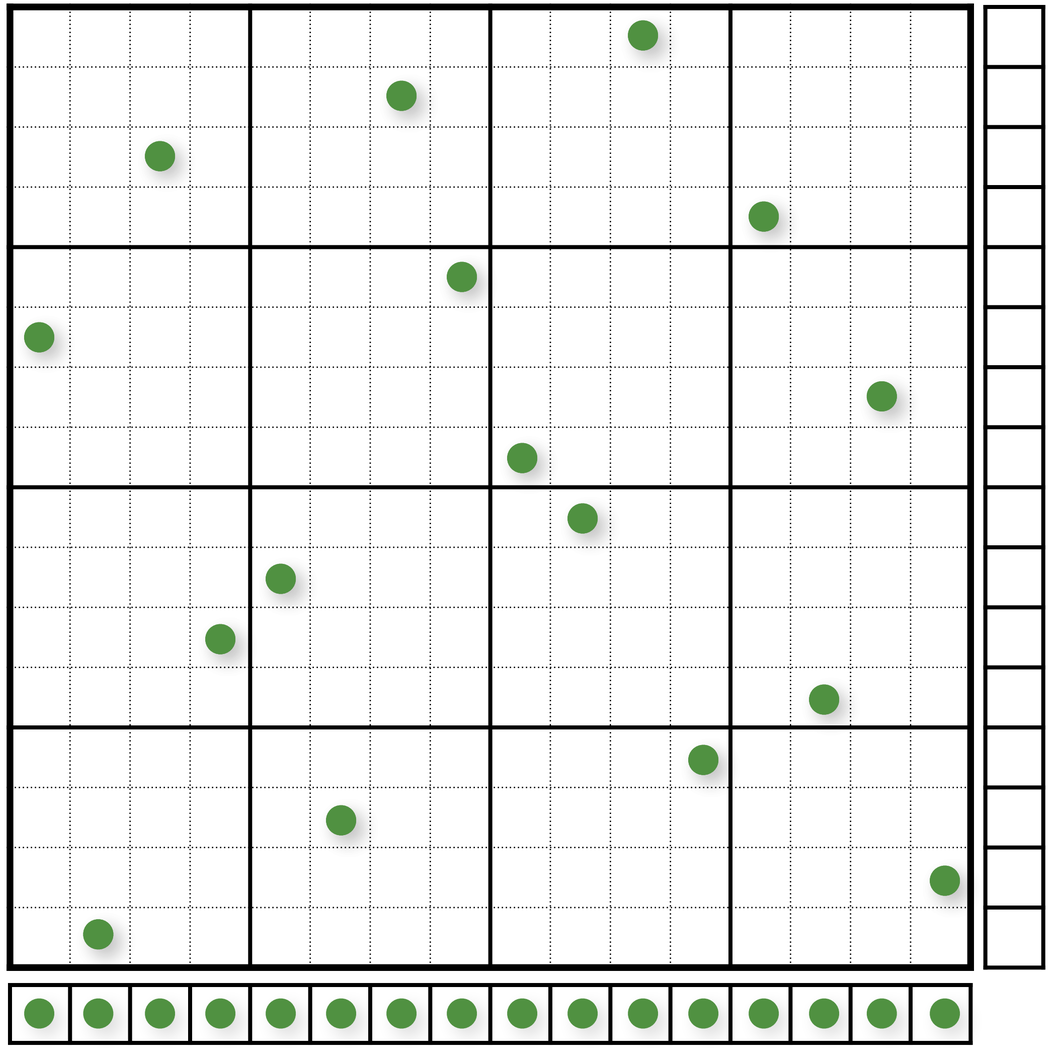
Multi-Jittered Sampling (Projections)



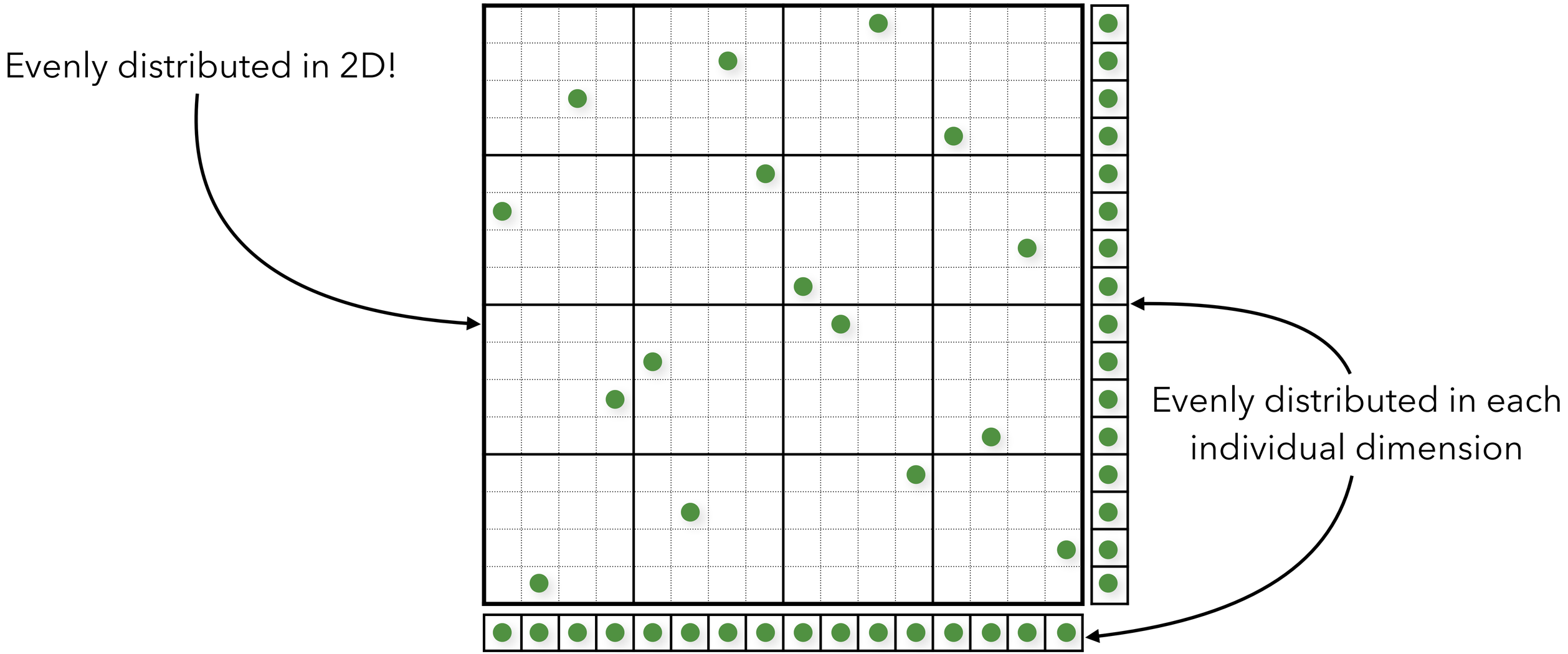
Multi-Jittered Sampling (Projections)



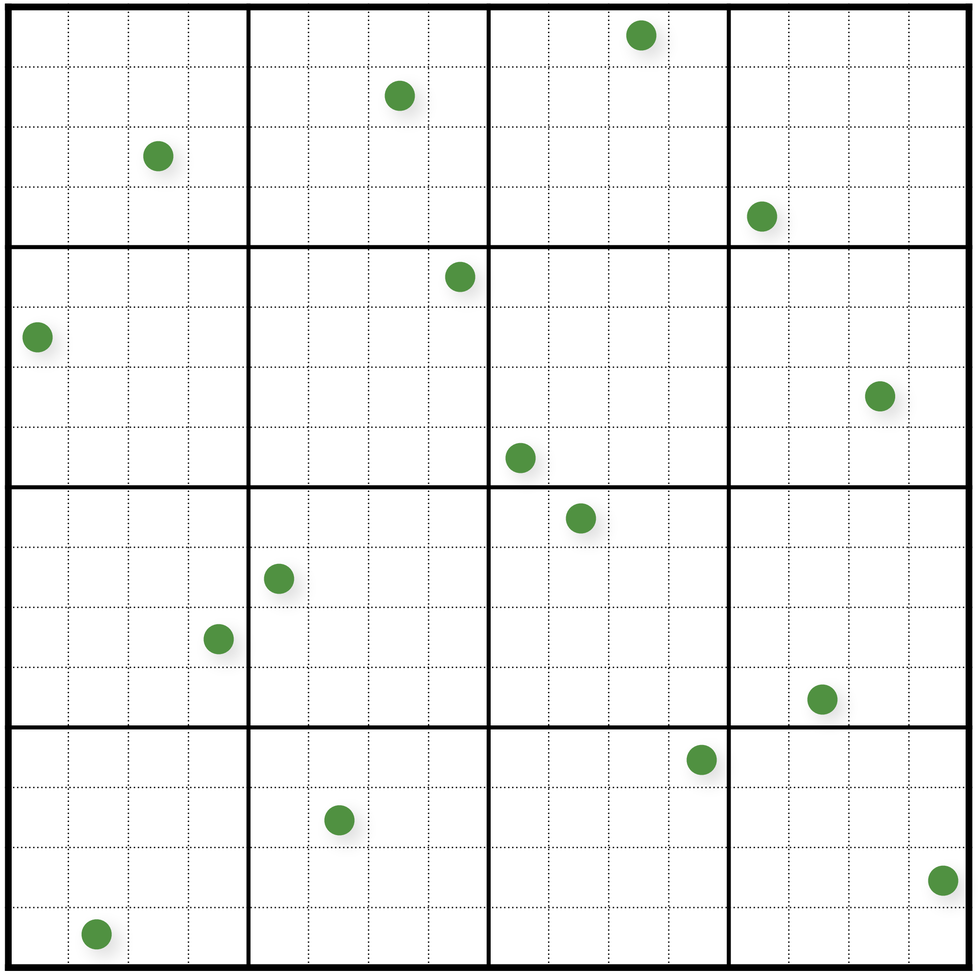
Multi-Jittered Sampling (Projections)



Multi-Jittered Sampling (Projections)



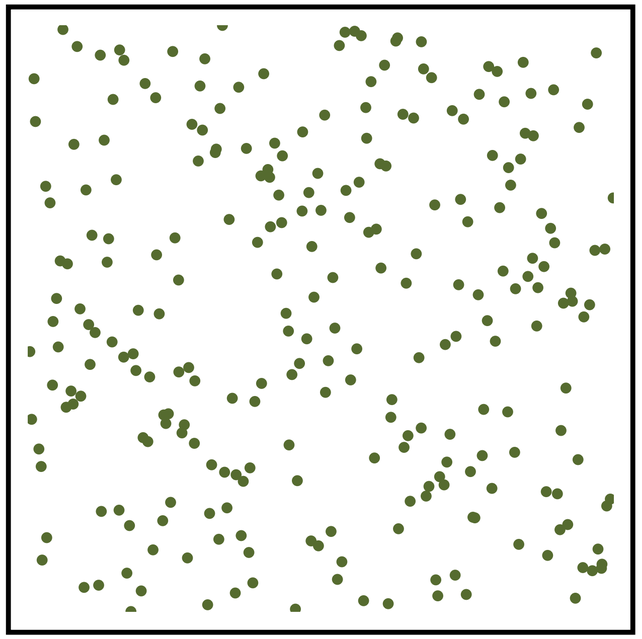
Multi-Jittered Sampling (Sudoku)



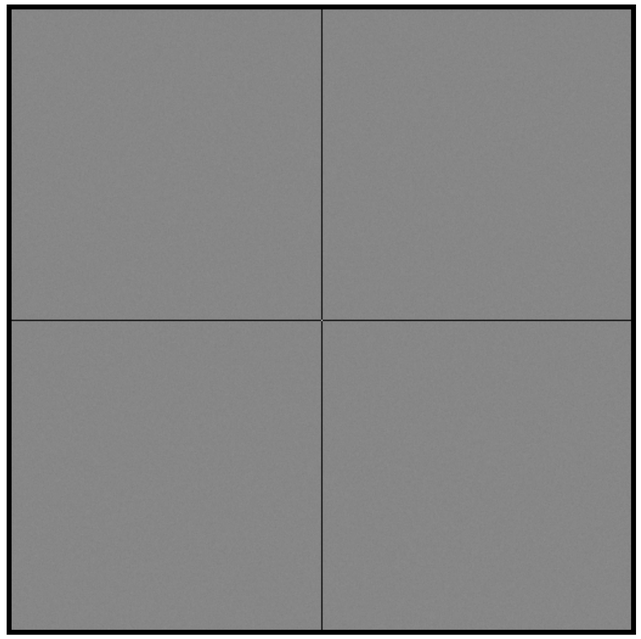
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
9	10	11	12	1	2	3	4	13	14	15	16	5	6	7	8
5	6	7	8	13	14	15	16	1	2	3	4	9	10	11	12
13	14	15	16	9	10	11	12	5	6	7	8	1	2	3	4
3	1	4	2	7	5	8	6	11	9	14	10	15	12	16	13
11	9	14	10	3	1	4	2	15	12	16	13	7	5	8	6
7	5	8	6	15	12	16	13	3	1	4	2	11	9	14	10
15	12	16	13	11	9	14	10	7	5	8	6	3	1	4	2
2	4	1	3	6	8	5	7	10	15	9	11	12	16	13	14
10	15	9	11	2	4	1	3	12	16	13	14	6	8	5	7
6	8	5	7	12	16	13	14	2	4	1	3	10	15	9	11
12	16	13	14	10	15	9	11	6	8	5	7	2	4	1	3
4	3	2	1	8	7	6	5	14	11	10	9	16	13	12	15
14	11	10	9	4	3	2	1	16	13	12	15	8	7	6	5
8	7	6	5	16	13	12	15	4	3	2	1	14	11	10	9
16	13	12	15	14	11	10	9	8	7	6	5	4	3	2	1

N-Rooks Sampling

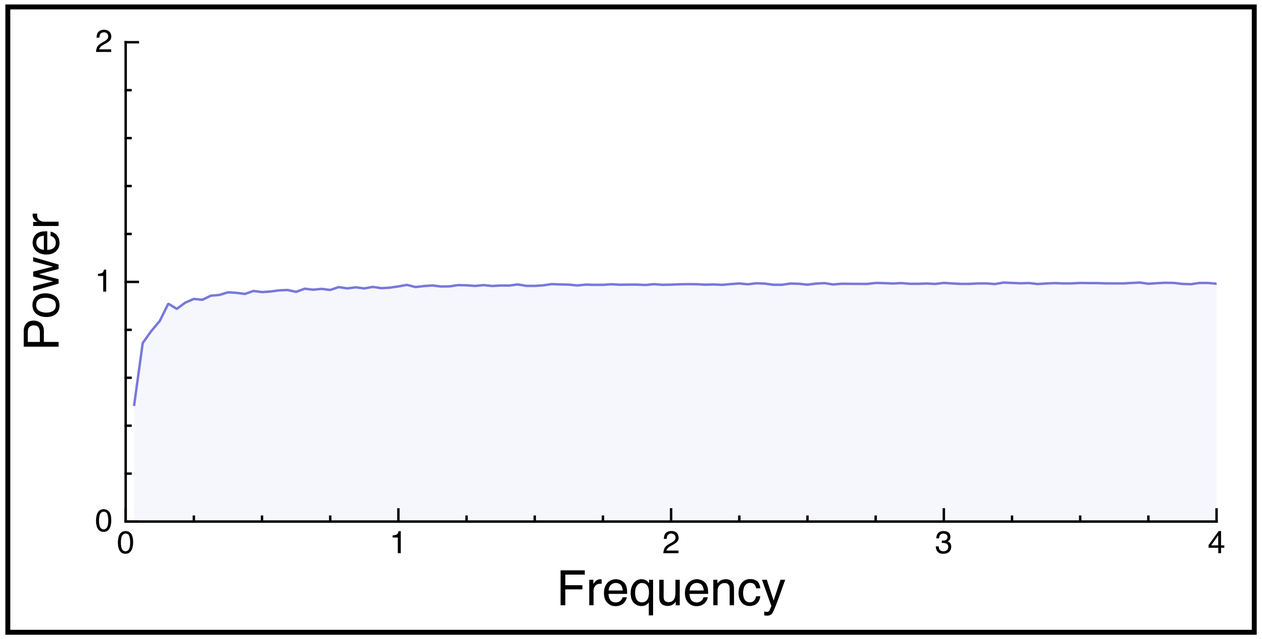
Samples



Power spectrum

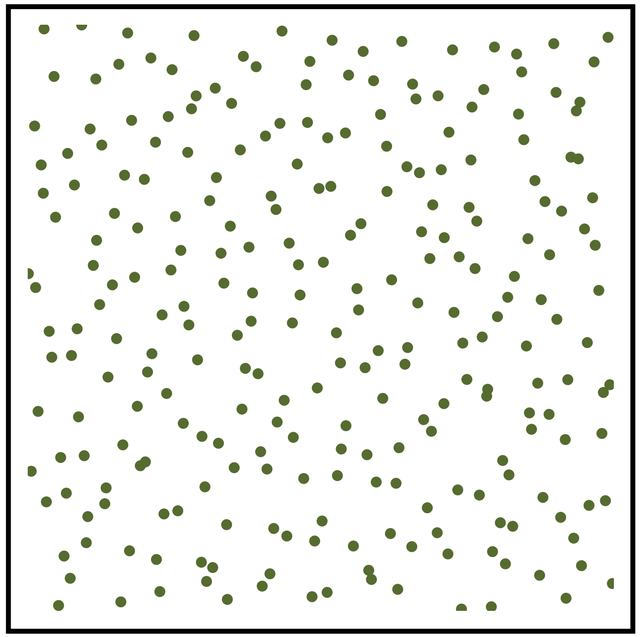


Radial mean

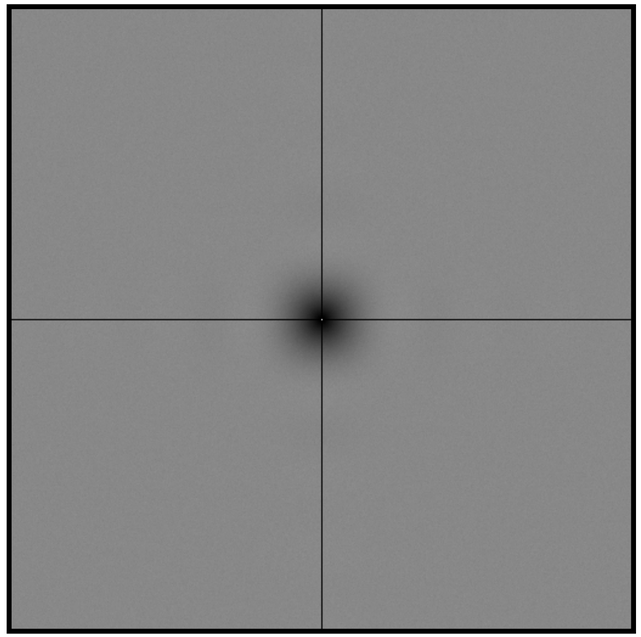


Multi-Jittered Sampling

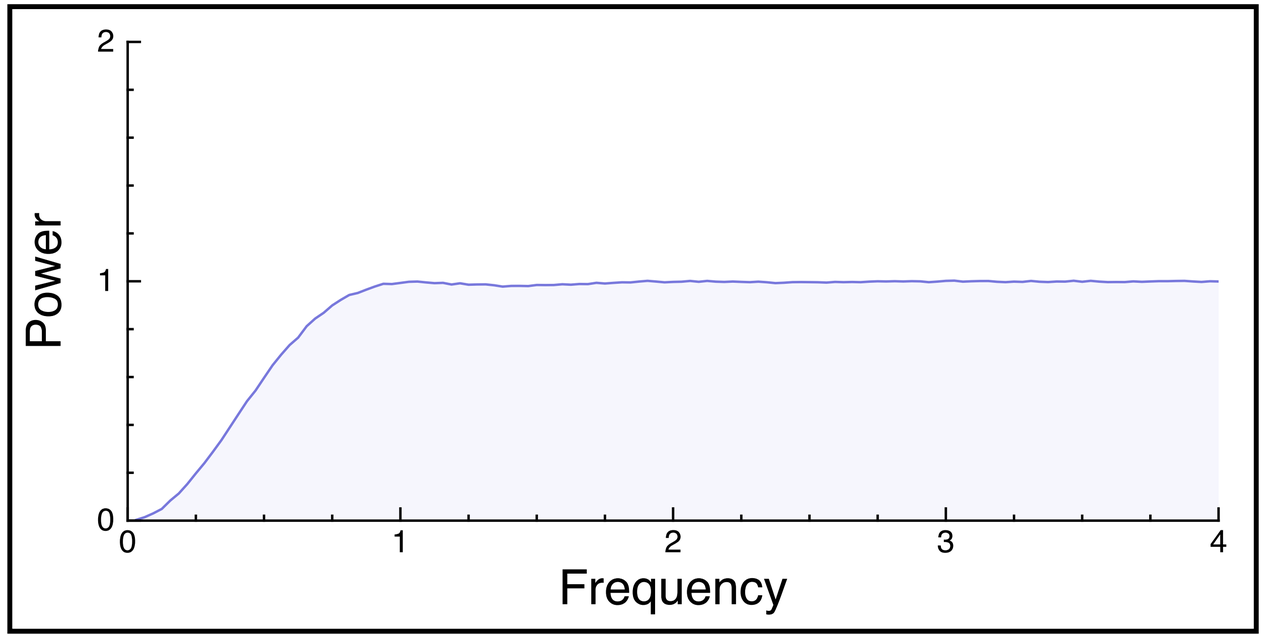
Samples



Power spectrum

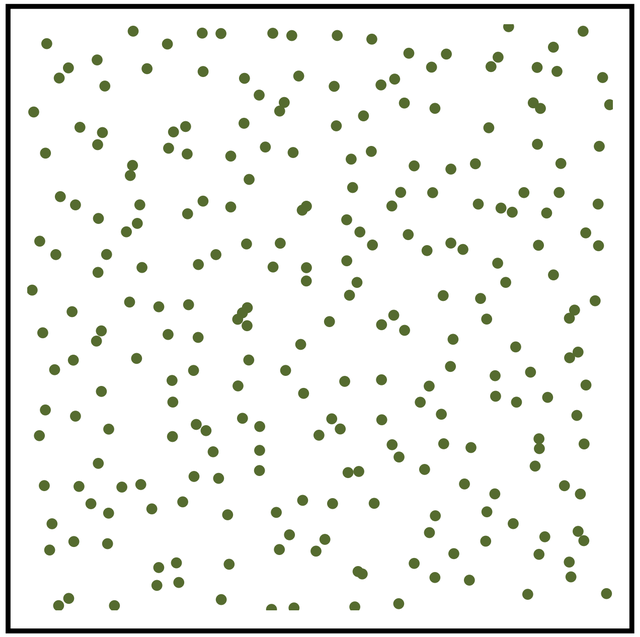


Radial mean

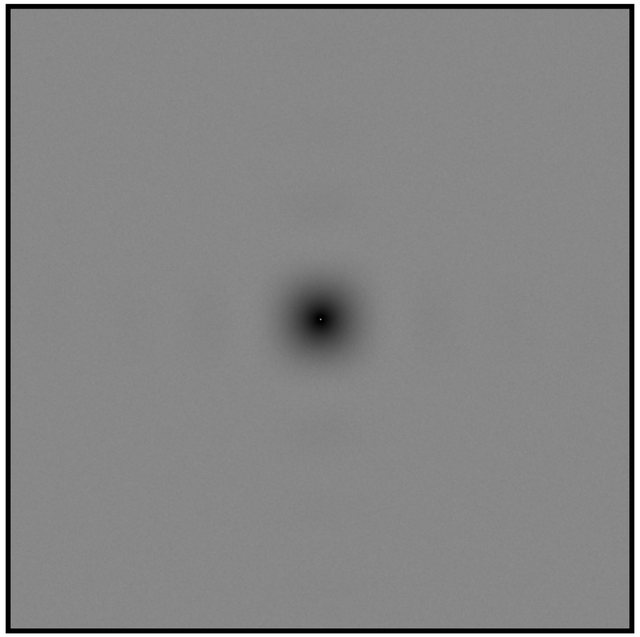


Jittered/Stratified Sampling

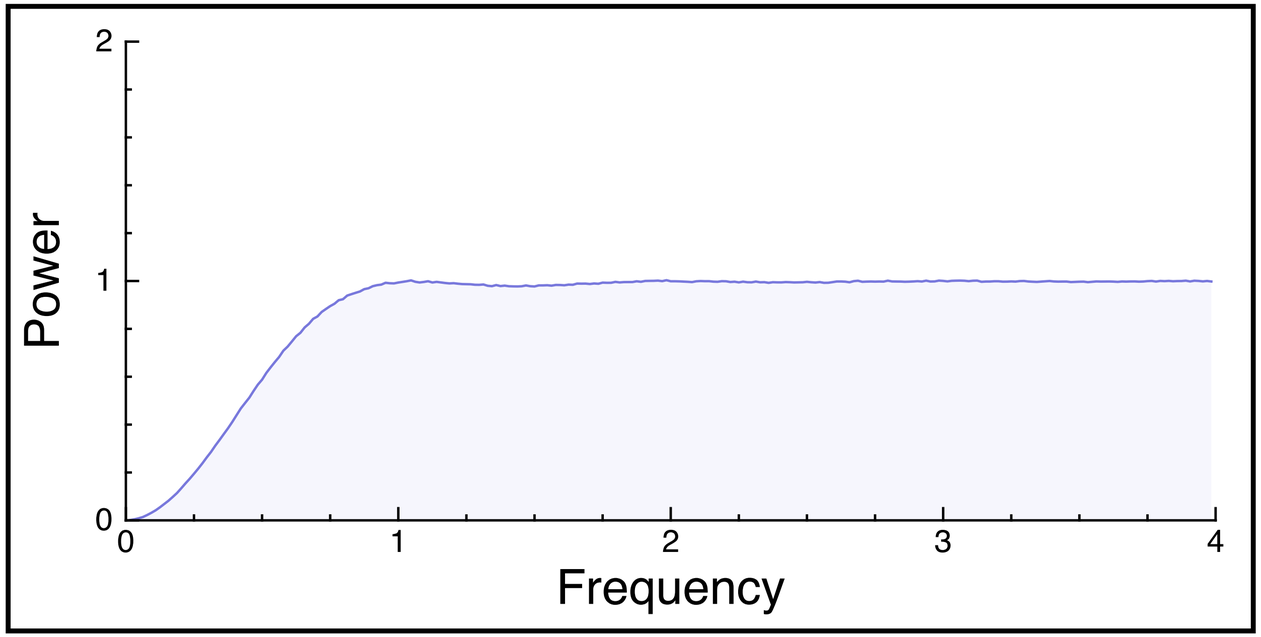
Samples



Power spectrum



Radial mean



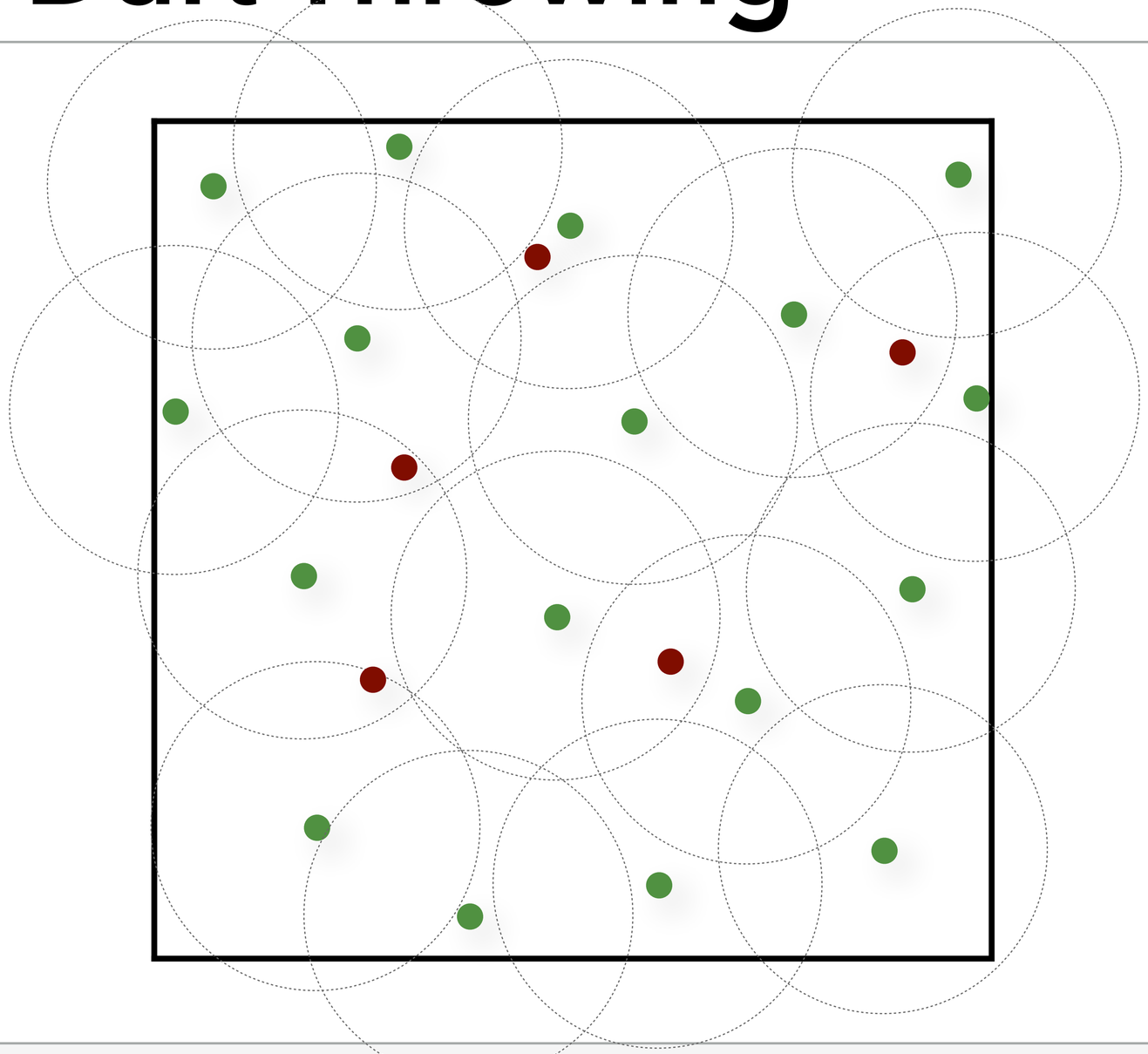
Poisson-Disk/Blue-Noise Sampling

Enforce a minimum distance between points

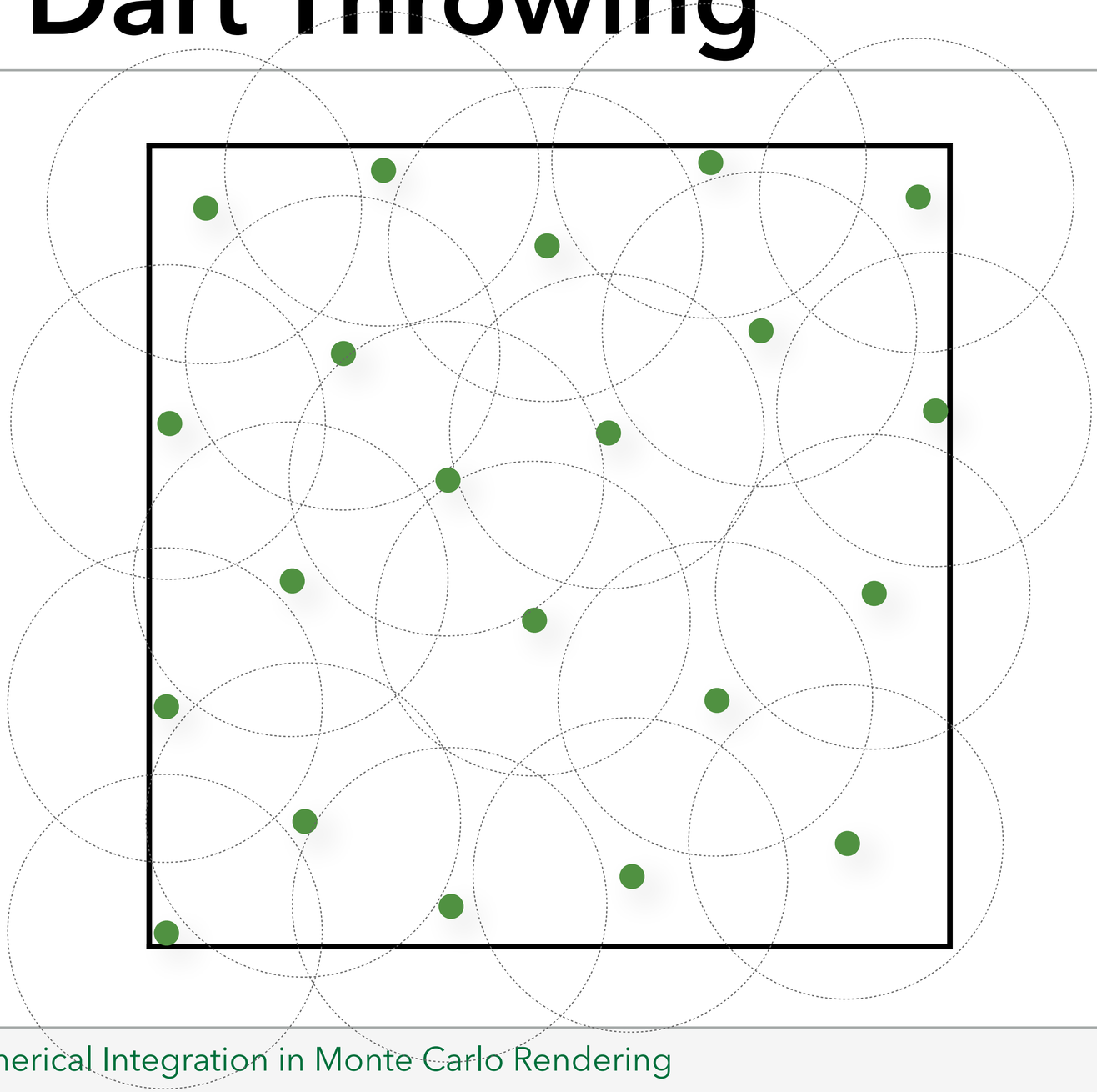
Poisson-Disk Sampling:

- Robert L. Cook. “Stochastic sampling in computer graphics.” ACM Transactions on Graphics. 1986.
- Ares Lagae and Philip Dutré. “A comparison of methods for generating Poisson disk distributions.” Computer Graphics Forum, 2008.

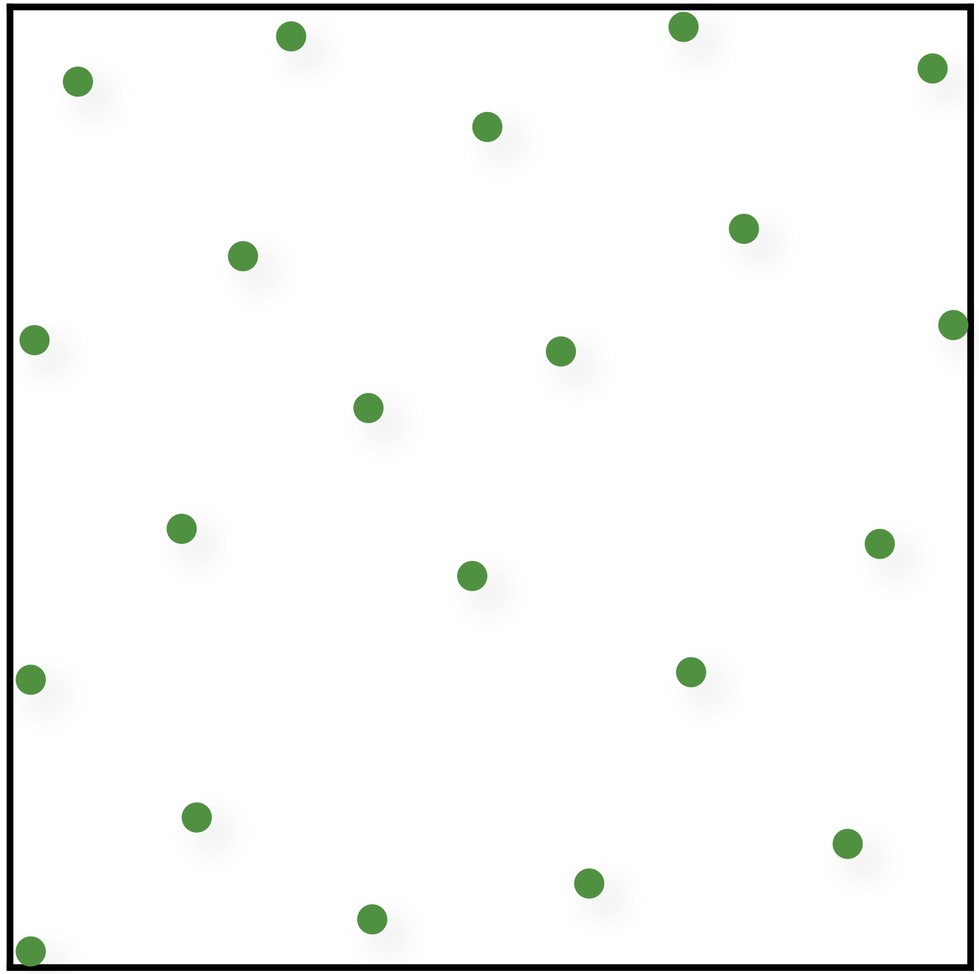
Random Dart Throwing



Random Dart Throwing

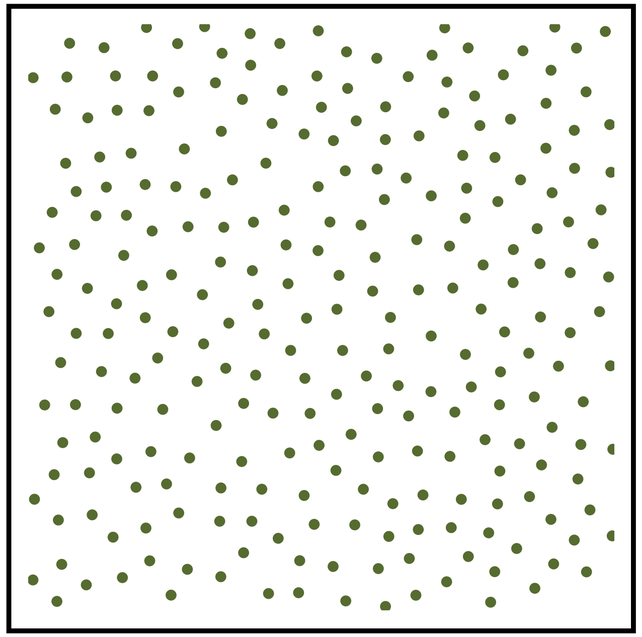


Random Dart Throwing

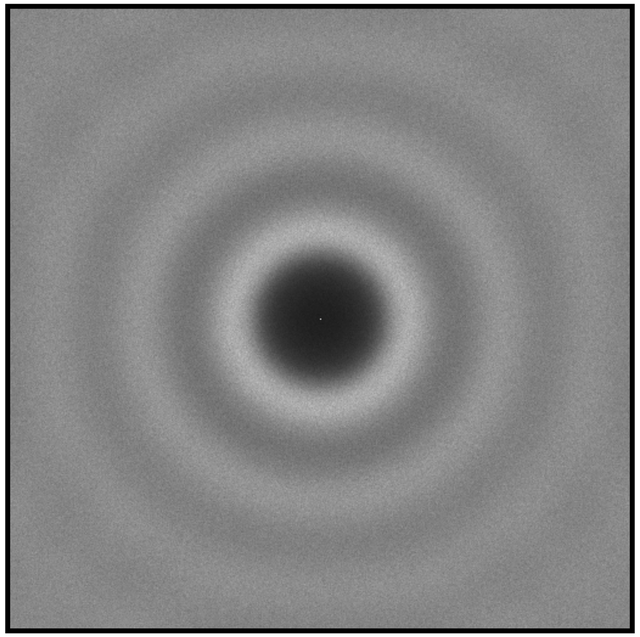


Poisson Disk Sampling

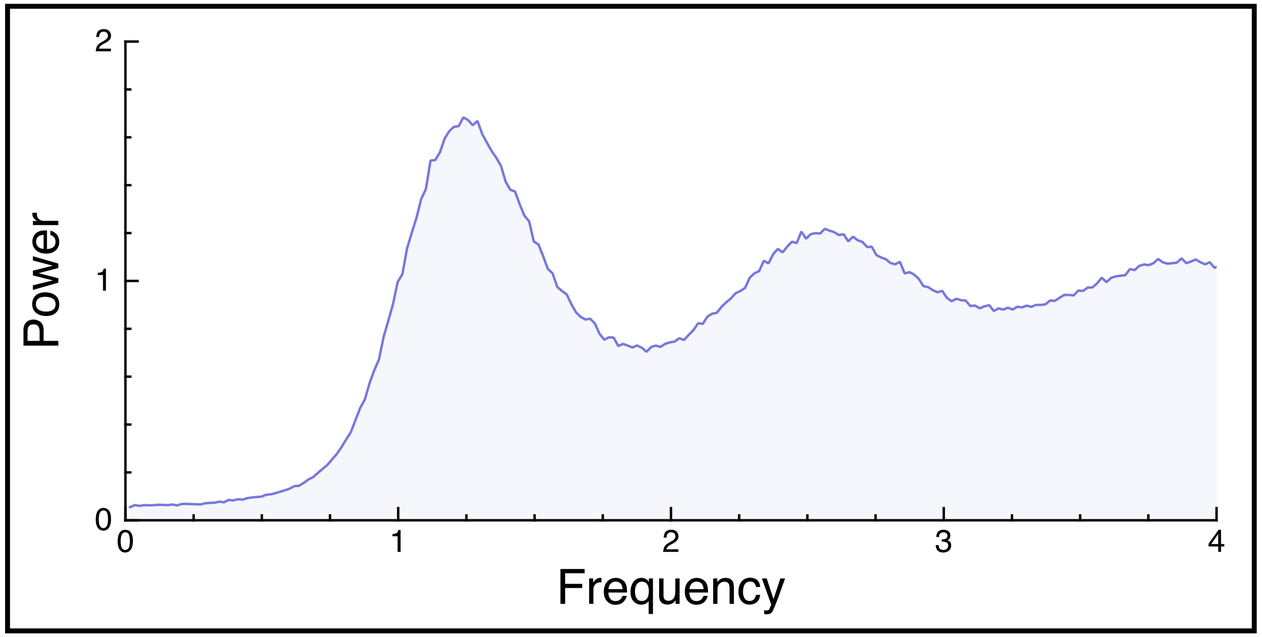
Samples



Power spectrum



Radial mean

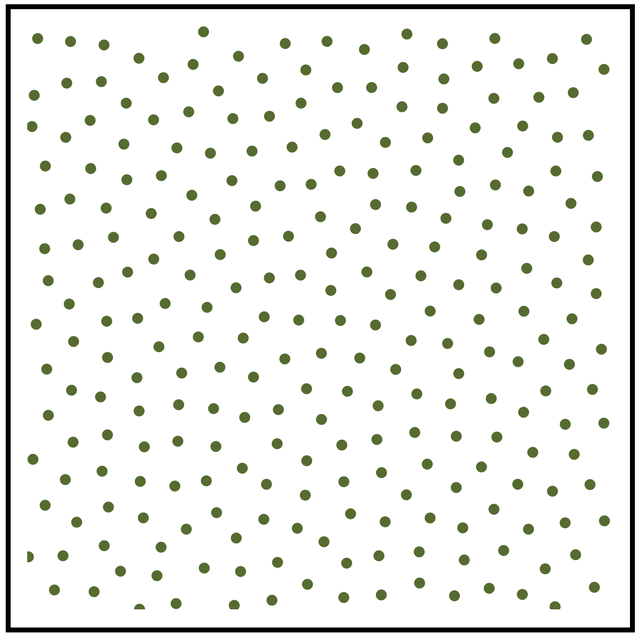


Blue-Noise Sampling (Relaxation-based)

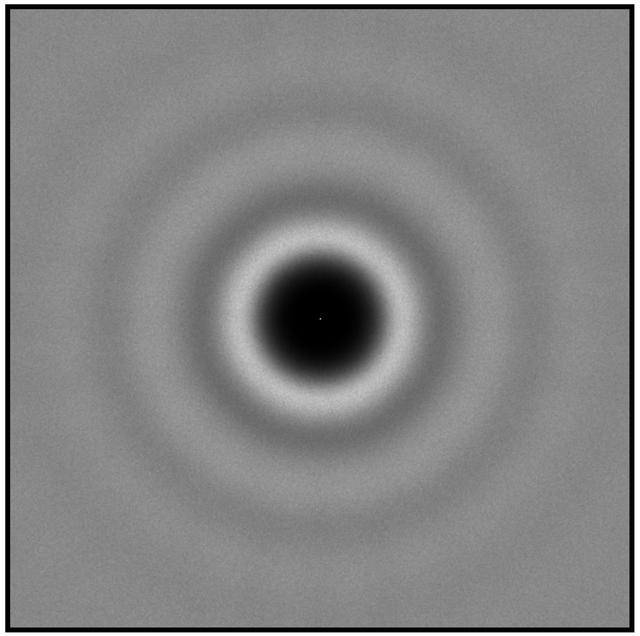
1. Initialize sample positions (e.g. random)
2. Use an iterative relaxation to move samples away from each other.

CCVT Sampling [Balzer et al. 2009]

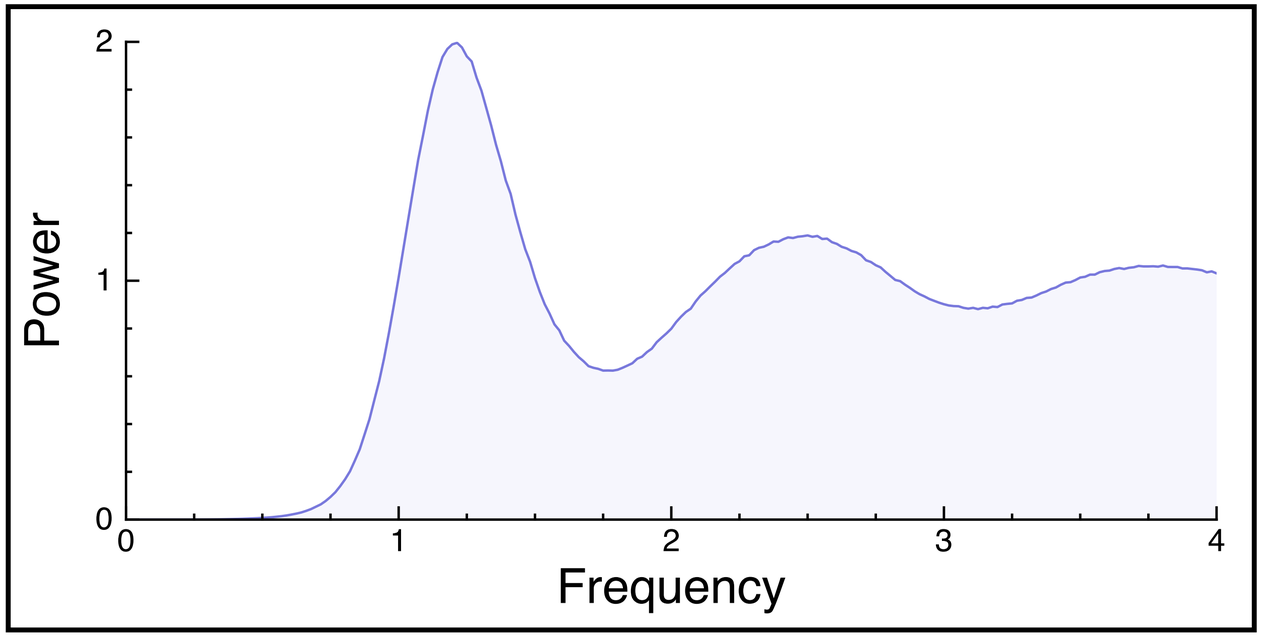
Samples



Power spectrum

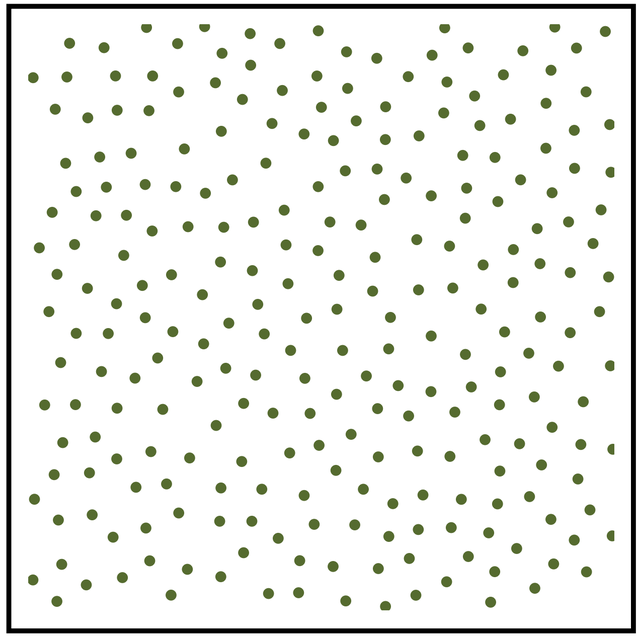


Radial mean

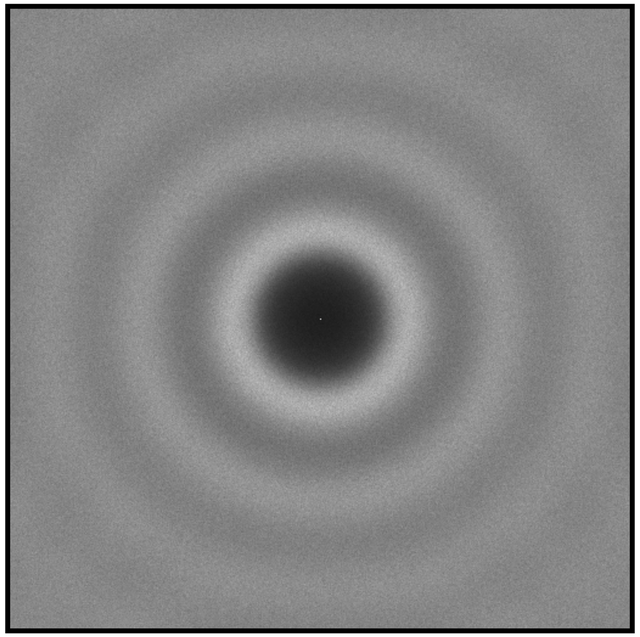


Poisson Disk Sampling

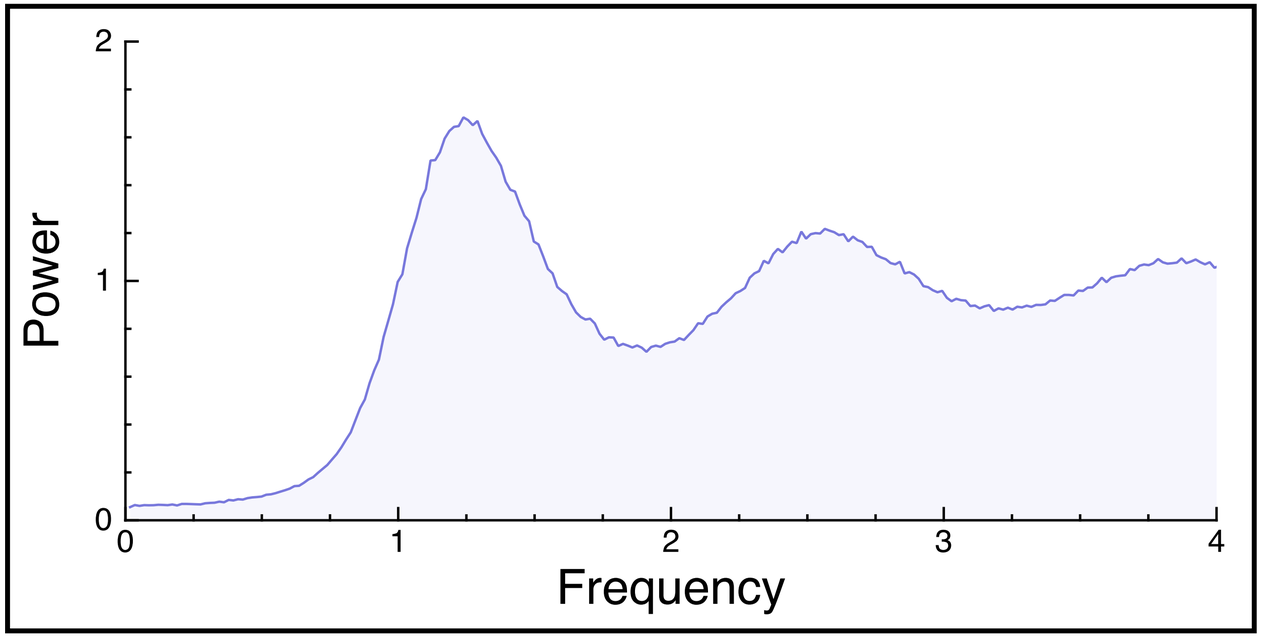
Samples



Power spectrum



Radial mean



Low-Discrepancy Sampling

Discrepancy is a measure of how “evenly spaced” samples are

Low-Discrepancy point sequences are deterministic sets of points specially crafted to be evenly distributed (have small discrepancy).

Entire field of study called Quasi-Monte Carlo (QMC)

The Van der Corput Sequence

Radical Inverse Φ_b in base 2

Subsequent points “fall into biggest holes”

n	Base 2	Φ_b
1	1	.1 = 1/2
2	10	.01 = 1/4
3	11	.11 = 3/4
4	100	.001 = 1/8
5	101	.101 = 5/8
6	110	.011 = 3/8
7	111	.111 = 7/8
…		

The Radical Inverse (Base 2)

```
float vanDerCorputRIU(uint n)
{
  n = (n << 16) | (n >> 16);
  n = ((n & 0x00ff00ff) << 8) | ((n & 0xff00ff00) >> 8);
  n = ((n & 0x0f0f0f0f) << 4) | ((n & 0xf0f0f0f0) >> 4);
  n = ((n & 0x33333333) << 2) | ((n & 0xcccccccc) >> 2);
  n = ((n & 0x55555555) << 1) | ((n & 0xaaaaaaaa) >> 1);
  return n / float (0x100000000LL);
}
```

The Halton Sequence

An n-dimensional Halton sequence uses the radical inverse with a different base b for each dimension:

$$x_i = (\Phi_2(i), \Phi_3(i), \Phi_5(i), \ldots, \Phi_{p_n}(i))$$

The bases should all be relatively prime.

Incremental/progressive generation of samples

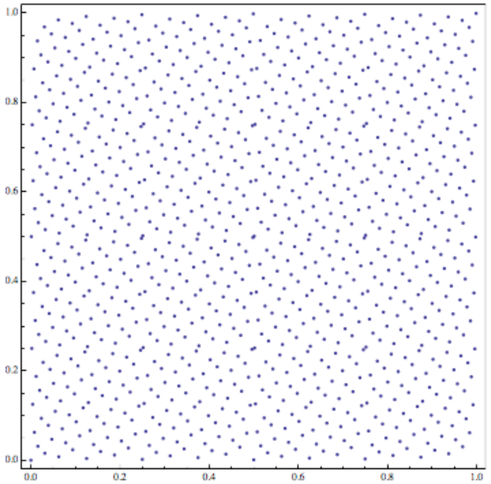
The Hammersley Sequence

Same as Halton, but uses i/N for first dimension:

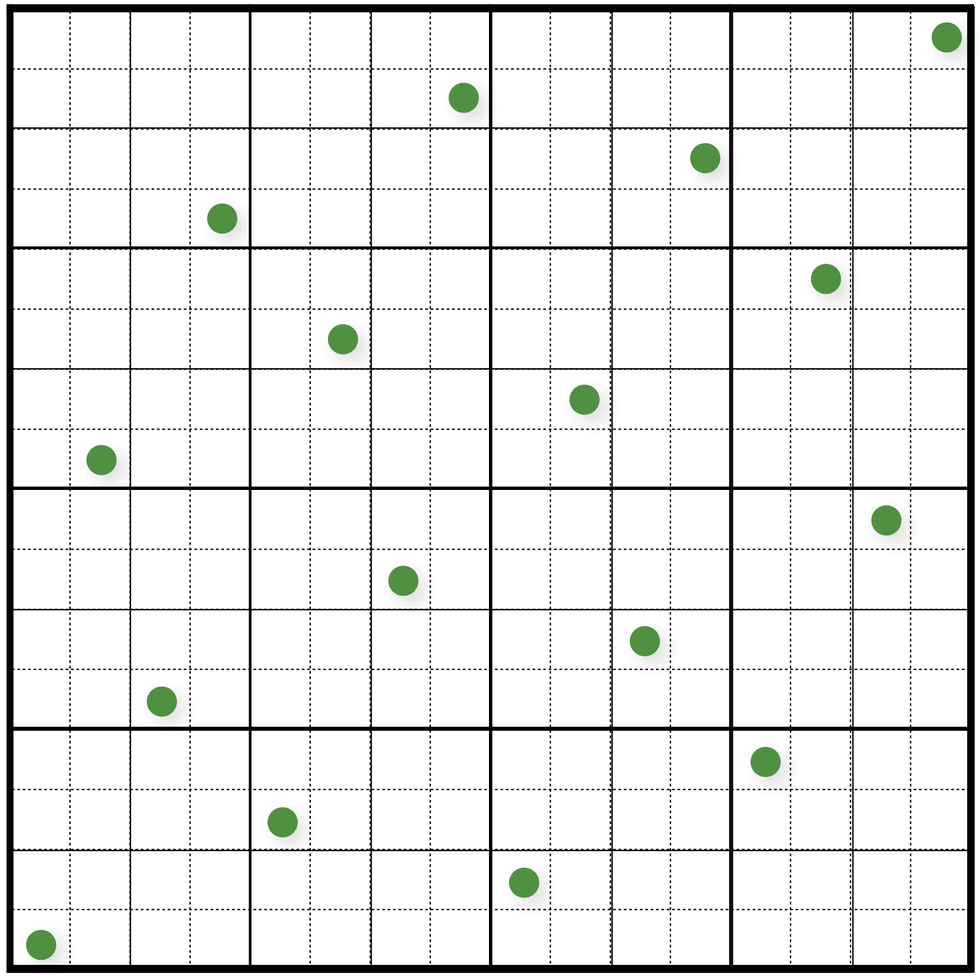
$$x_i = \left(\frac{i}{N}, \Phi_2(i), \Phi_3(i), \ldots, \Phi_{p_n}(i) \right)$$

Provides slightly lower discrepancy

Not incremental, need to know total number of samples, N, in advance

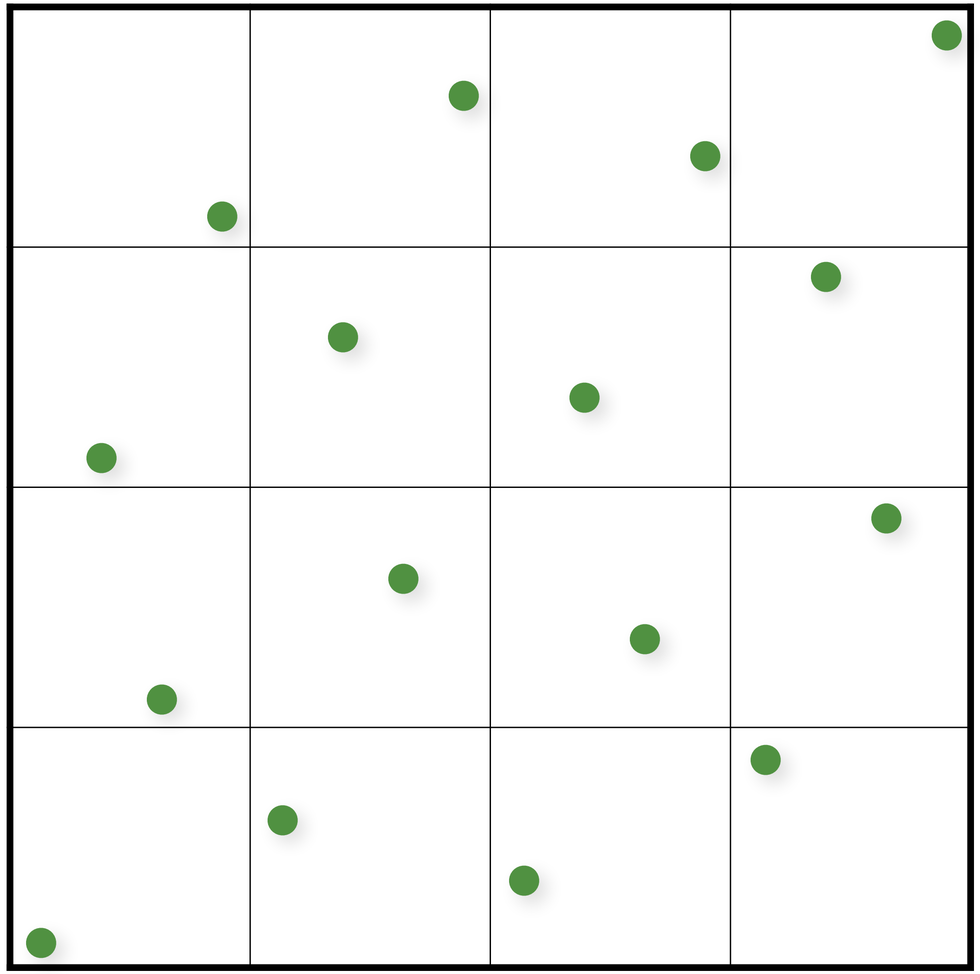


The Hammersley Sequence



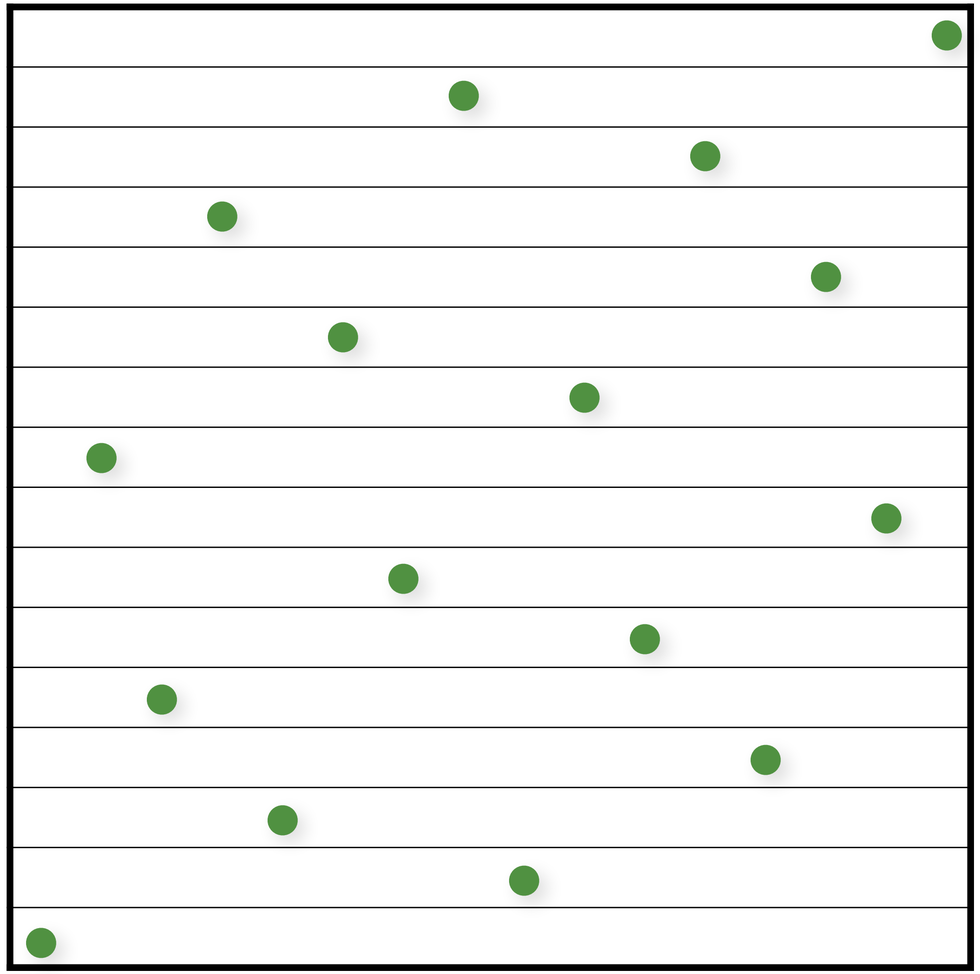
1 sample in each “elementary interval”

The Hammersley Sequence



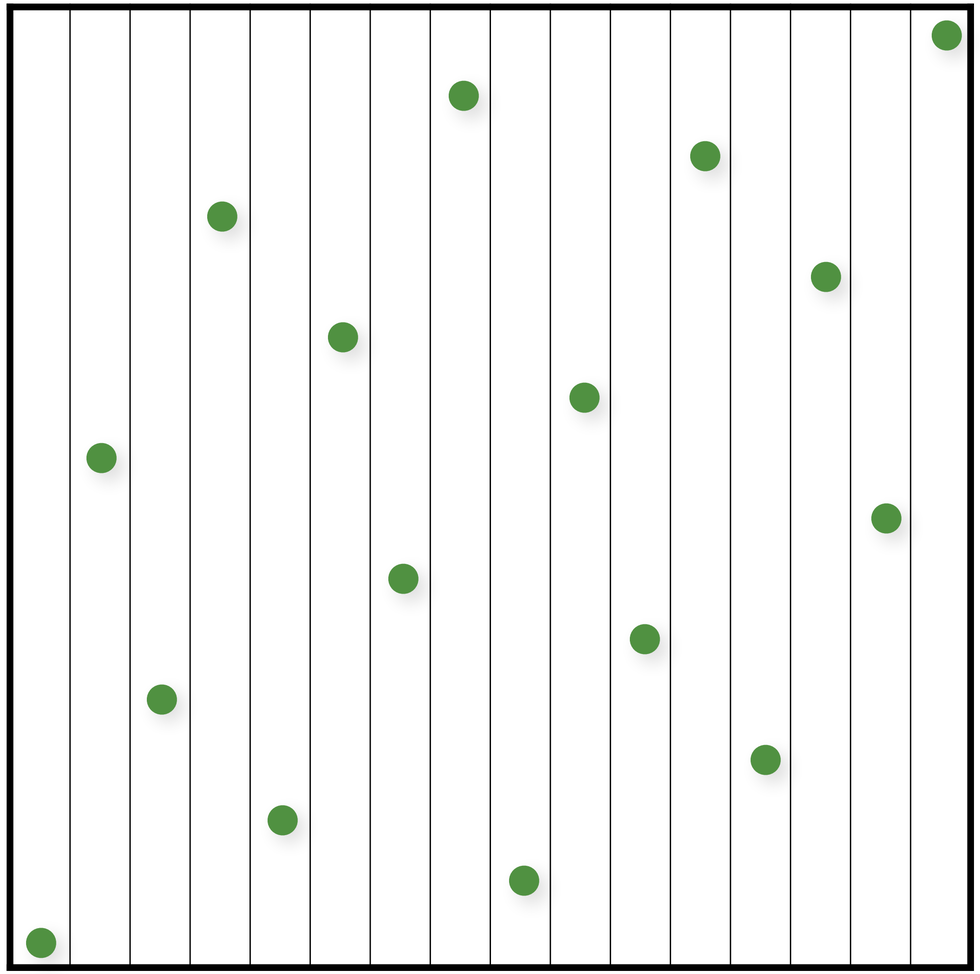
1 sample in each “elementary interval”

The Hammersley Sequence



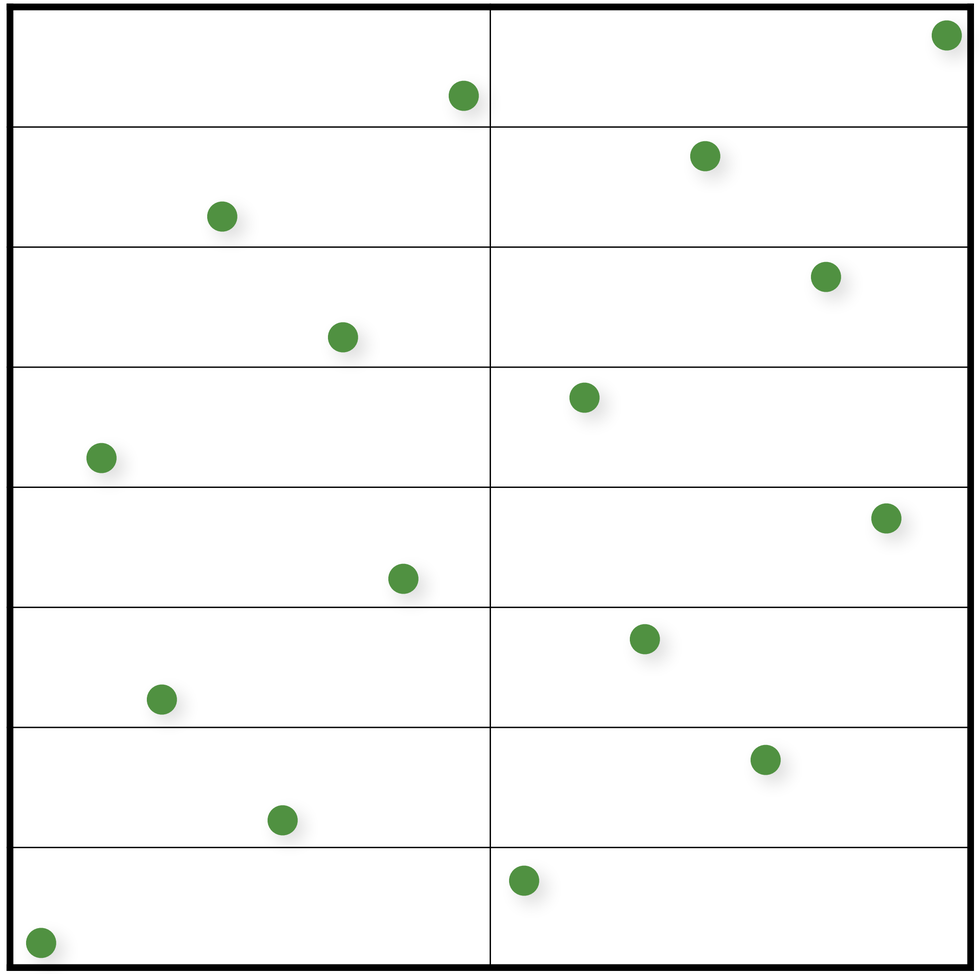
1 sample in each “elementary interval”

The Hammersley Sequence



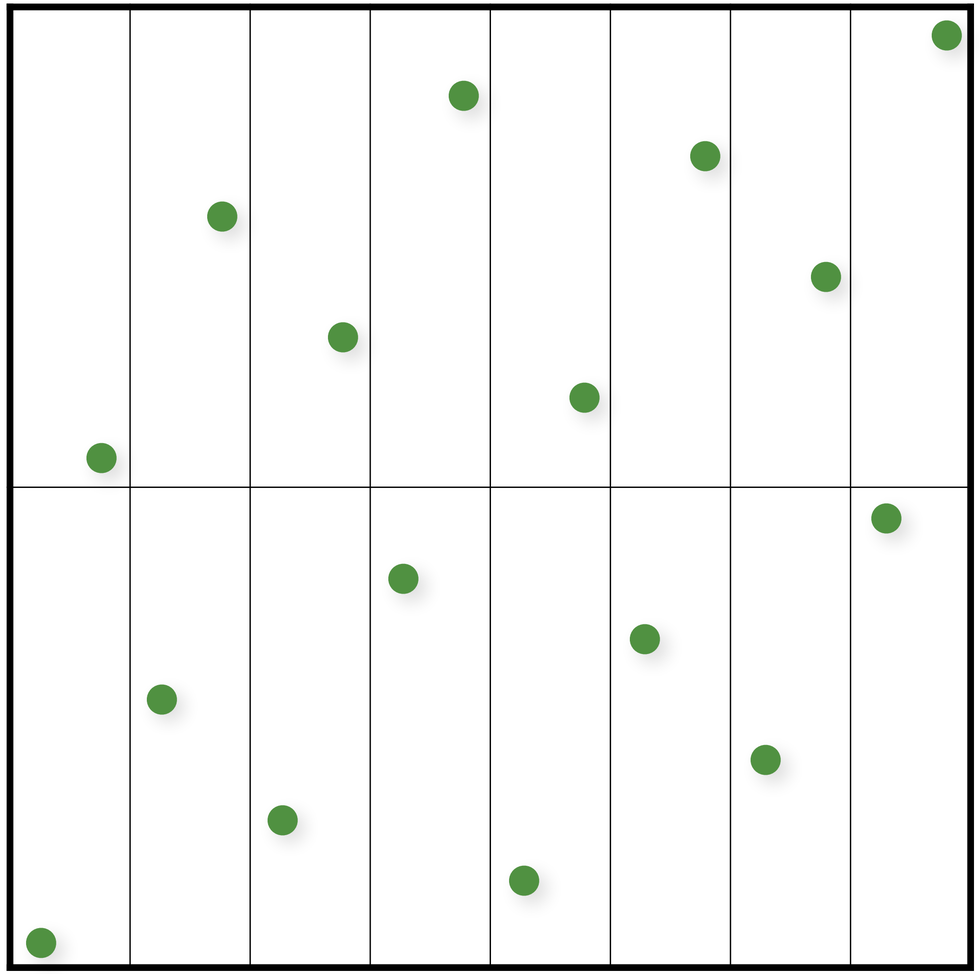
1 sample in each “elementary interval”

The Hammersley Sequence



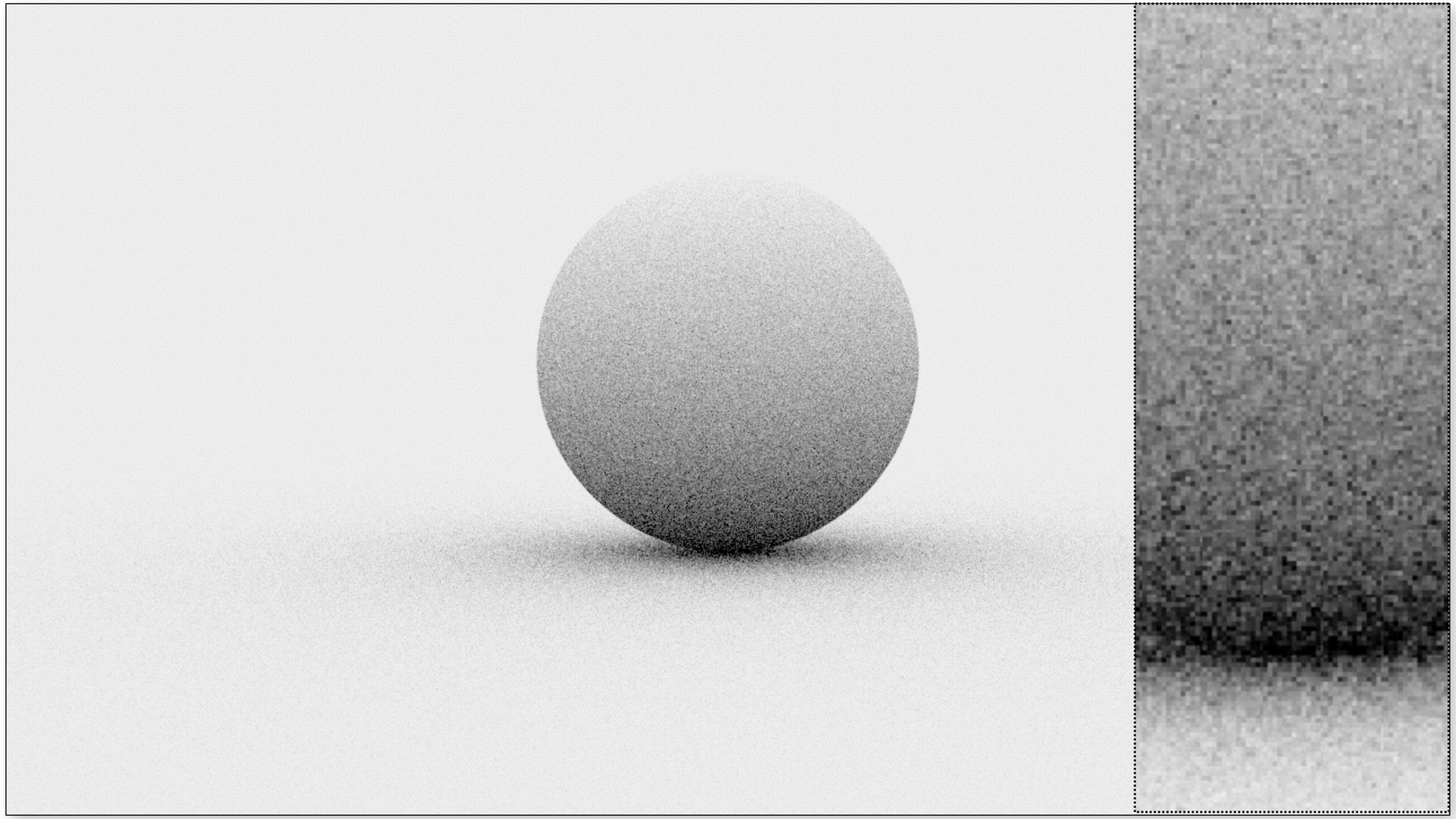
1 sample in each “elementary interval”

The Hammersley Sequence

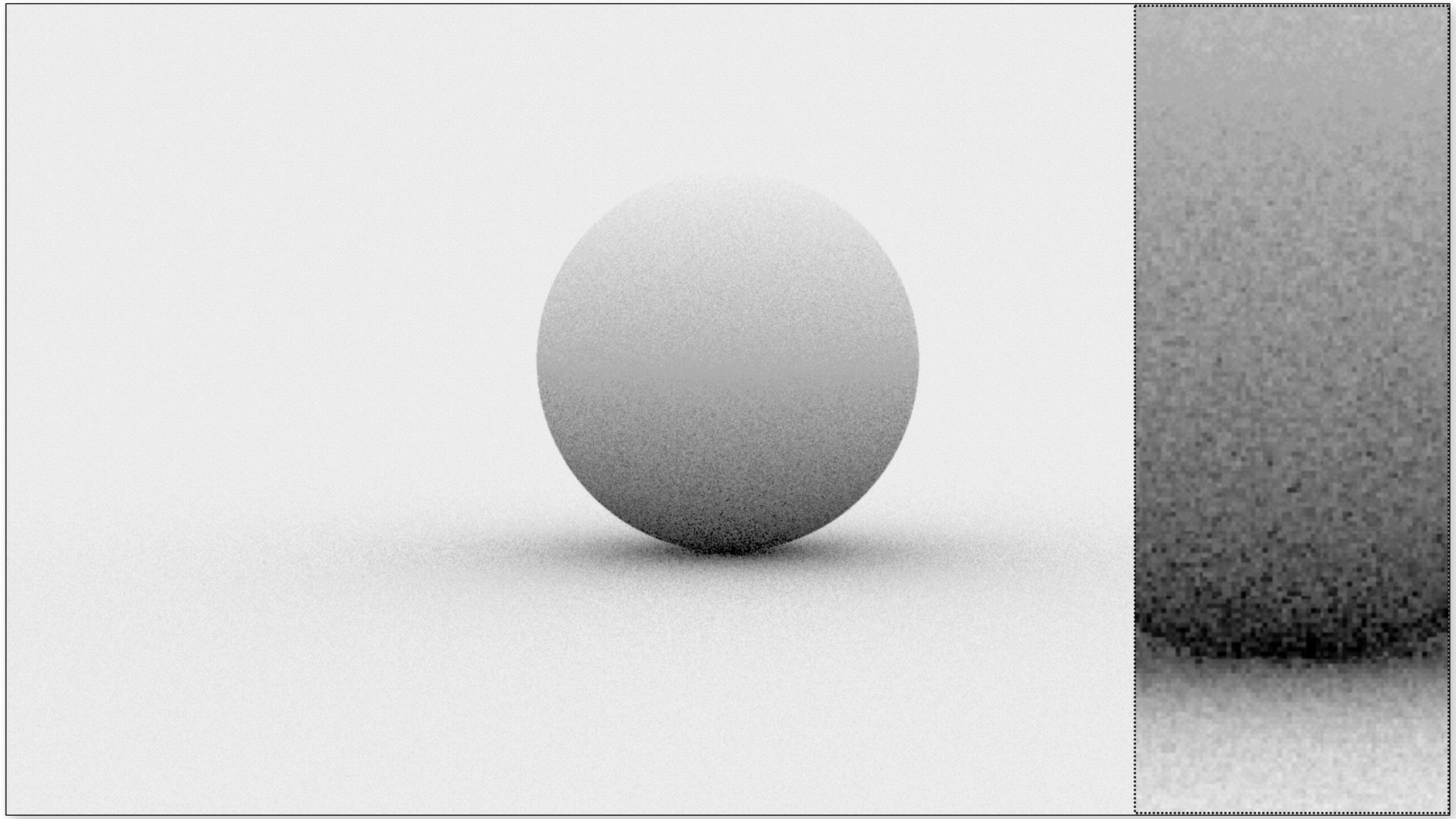


1 sample in each “elementary interval”

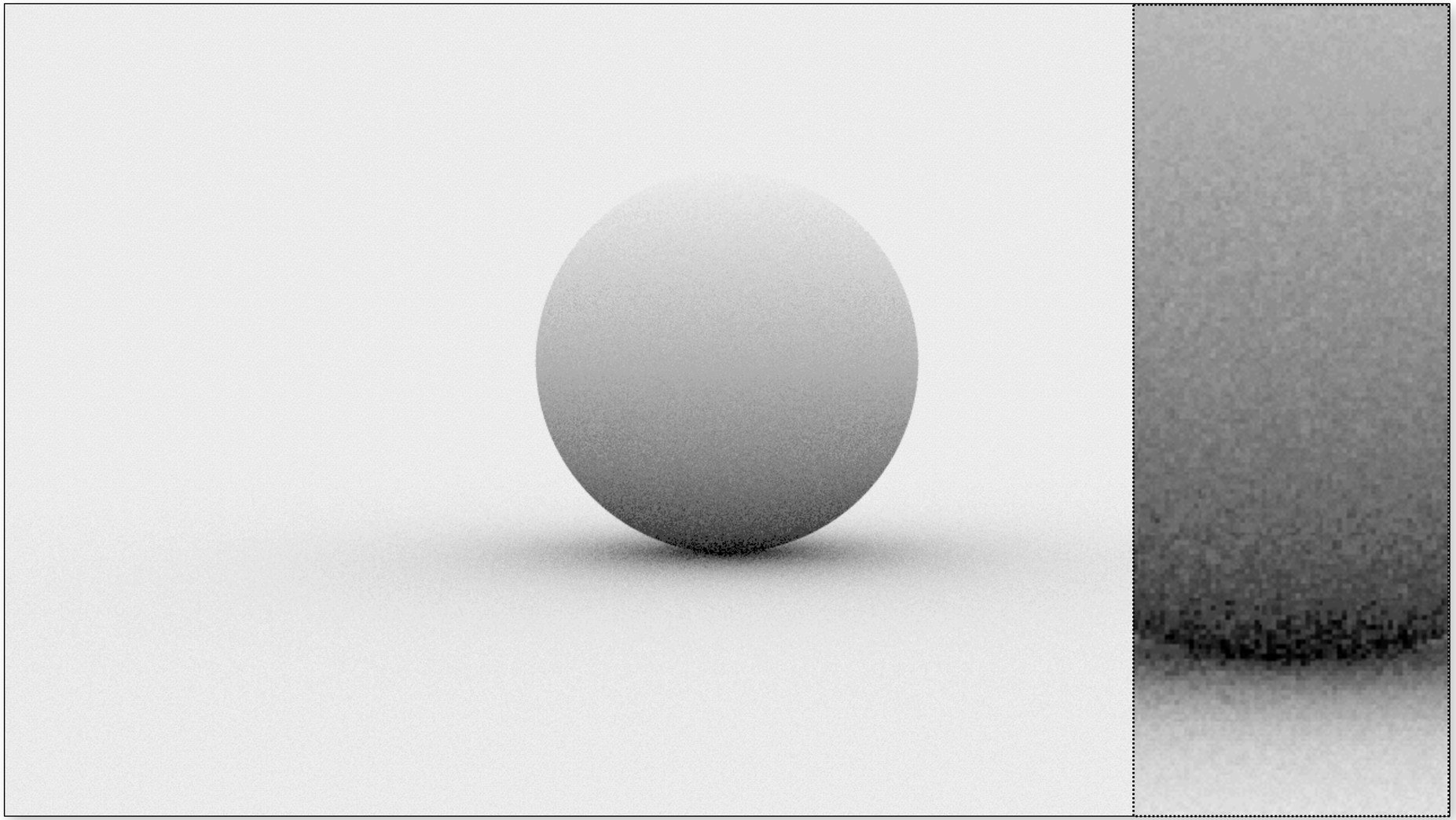
Monte Carlo (16 random samples)



Monte Carlo (16 stratified samples)



Scrambled Hammersley



Many more...

Sobol

Faure

Larcher-Pillichshammer

Folded Radical Inverse

(t,s)-sequences & (t,m,s)-nets

Scrambling/randomization

much more...