



# LOW-DISCREPANCY BLUE NOISE SAMPLING

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Co-authored with

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## OVERVIEW

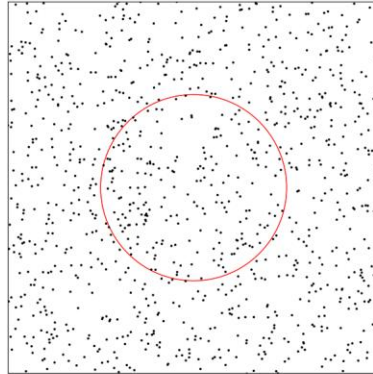


- Motivation and Concept
  - Monte Carlo Integration
  - Discrepancy
  - Blue Noise vs Low Discrepancy
  - Combining the two properties
  - Target-Matching Algorithm
- Low-Discrepancy Blue Noise Sampler
  - Performance
  - Limitations

## MONTE CARLO INTEGRATION

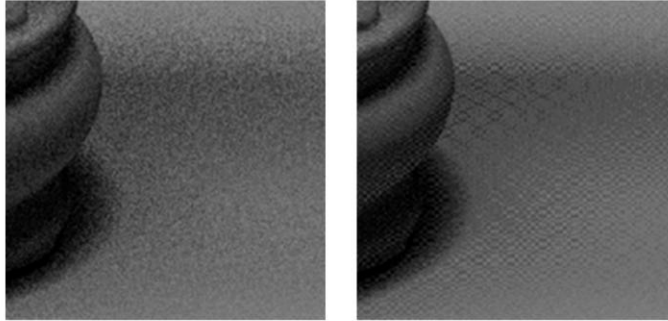


- We want to compute the area of the circle given the area of the box.
- In practice, the box could be a light source, and the circle is an object that hides (occludes) it.
- We randomly generate sample points in the box
- The percentage of the points inside the circle estimates the area of the circle relative to the box



## PRACTICAL ISSUES IN RENDERING

- Noise, due to high estimation errors
- Aliasing, due to correlated sampling



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Images are synthesized from samples

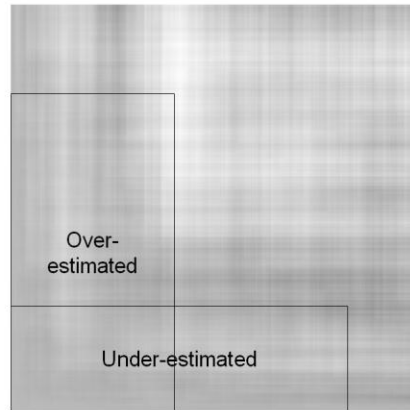
Rays are cast through image samples and traced to the scene

End-points of rays are traced to sample points on light sources to compute shadows

Millions of samples, efficiency is crucial!

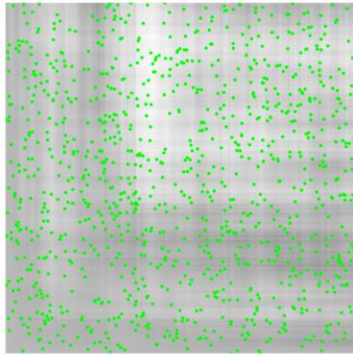
## DISCREPANCY

- Largest error in estimating the area of an axes-aligned rectangle
- Other shapes can be approximated with rectangles

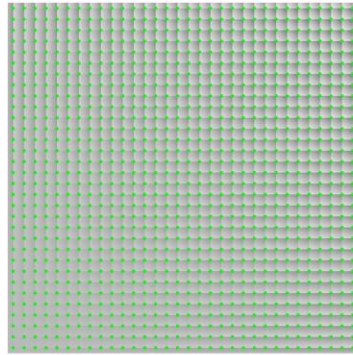


- Start discrepancy: rectangles anchored to origin.
- Star discrepancy is easier to compute, and can be associated with points, hence visualized as a map.

## EXAMPLES



**White Noise**



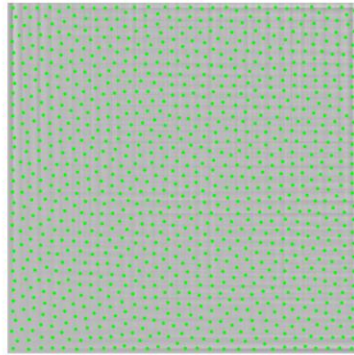
**Regular Grid**

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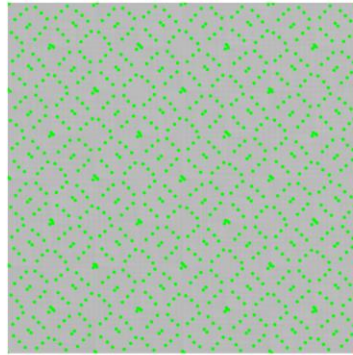


- White noise has excessively-large discrepancy, hence produces too much noise.
- Regular grid has a regular pattern of discrepancy, leading to aliased manifestation of error; e.g. bands of shadow.

## BLUE NOISE “OR” LOW-DISCREPANCY?



Organic

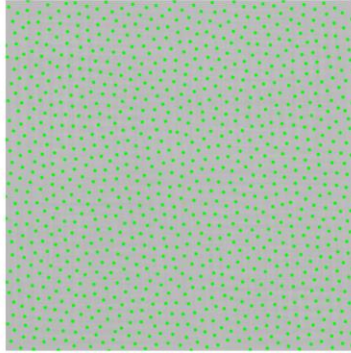


Synthetic



- We could do better than random: use evenly distributed point sets.
- Blue noise: even density, but otherwise random.
- Low-discrepancy: mathematically-computed, optimized for LD.
- Which sampling pattern would you prefer?
- Even in this room, some people might argue for blue noise, and others argue for low discrepancy.
- I may argue for BN for low sampling rates, and LD for high rates.

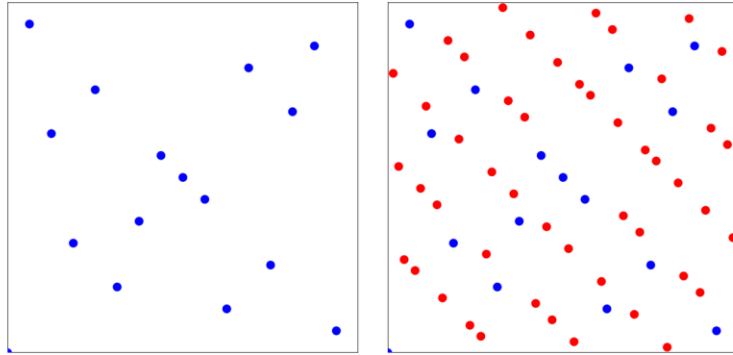
## BLUE NOISE “AND” LOW-DISCREPANCY!



But we no longer have to ask this question, because we managed to have BN and LD in the same point set?



## OPTIMIZING A LOW DISCREPANCY SET?



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- We may proceed by choosing a LD set/sequence, the deterministic side, and optimize it for BN.
- Existing LD constructions are topologically unstable: different neighbors for the same sample point, depending on the taken number of samples.



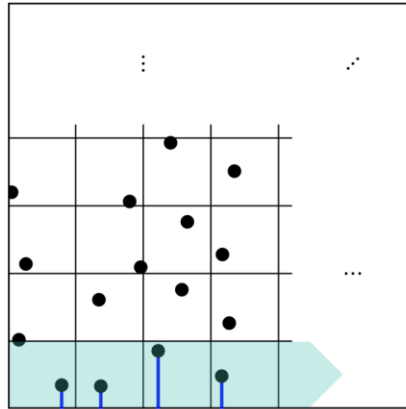
To combine blue noise and low discrepancy patterns we bring them to a common ground using stratification; that is, we start with a stratified LD and stratified blue noise sets, and try to align their points in each stratum.

## A NEW STRATIFIED LD CONSTRUCTION



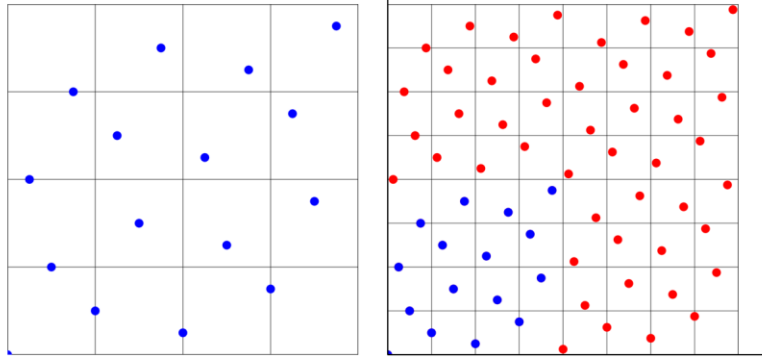
### THEOREM

The discrepancy of a 2D stratified point set is bounded by the discrepancy of the 1D sequences of offsets along rows and columns



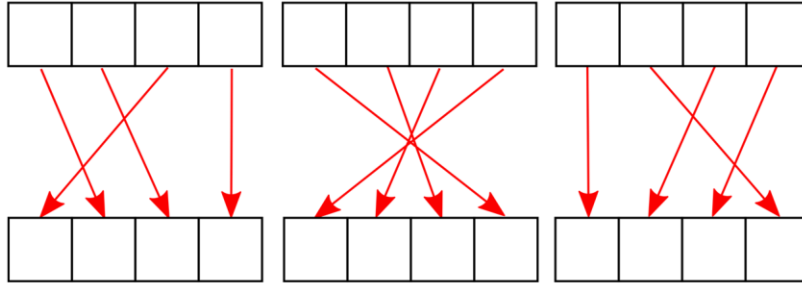
- We solved the topology problem with existing LD constructions by inventing a new LD construction.
- Consider a stratified point set like this: a regular lattice of cells, each cell hosting a single point.
- Look at the sequence of horizontal offsets over each and every column, and vertical offsets over each and every row.
- We proved that if all these sequences are LD sequences, then the point set is a LD point set.

## 2D INDEXED LD SETS



- Use LD sequences to supply the offsets. This one uses van der Corput sequence
- Same neighbors for same index.
- Infinite point set, slice and scale as needed!
- We can't just move the points, we have to preserve the LD sequence property along rows and columns.

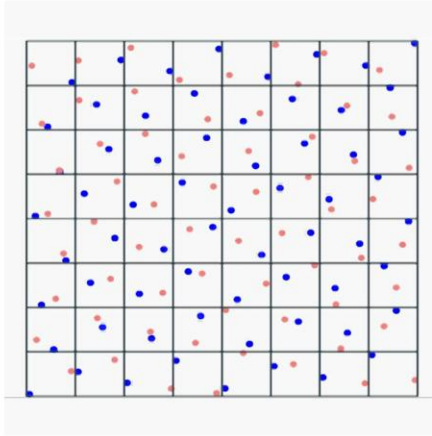
## DISCREPANCY-PRESERVING REARRANGEMENT



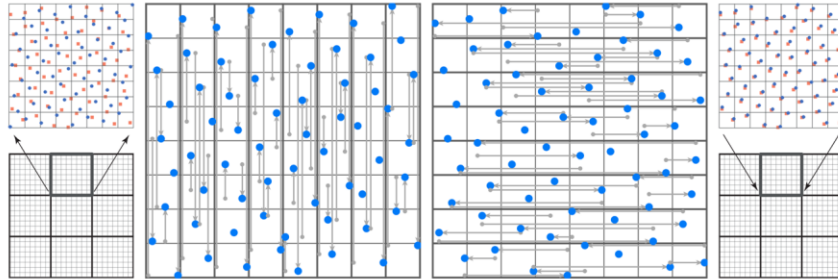
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- Optimization is possible via rearrangement.
- Reordering small chunks of entries in a LD sequence has little impact on discrepancy.

## AXIS-WISE 2D REARRANGEMENT DEMO

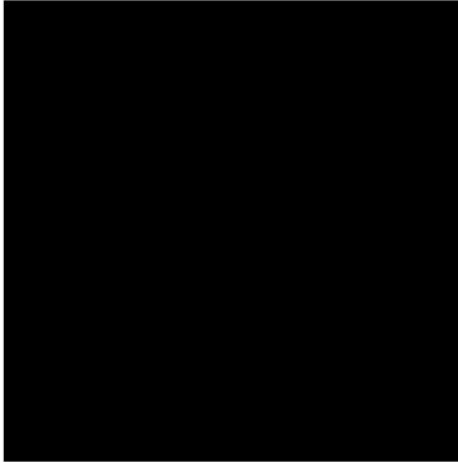


## REFERENCE-MATCHING ALGORITHM



- Take a stratified LD set as a reference.
- Reorder coordinates in small blocks of LD set to match the order of coordinates in the reference.
- Store the new order.
- Efficient storage: 1 byte per point.

DEMO







# LDBN SAMPLER

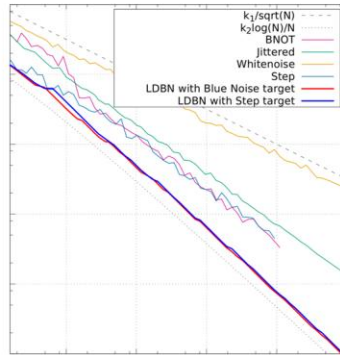
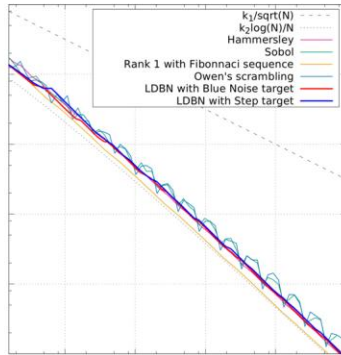
## PERFORMANCE DATASHEET

- Discrepancy:  $O(\log(N)/N)$
- Blue Noise Profiles: BNOT, Step, PPO
- Speed: 300~400 MPPS
- Memory Footprint: 16KB
- Adaptive: No

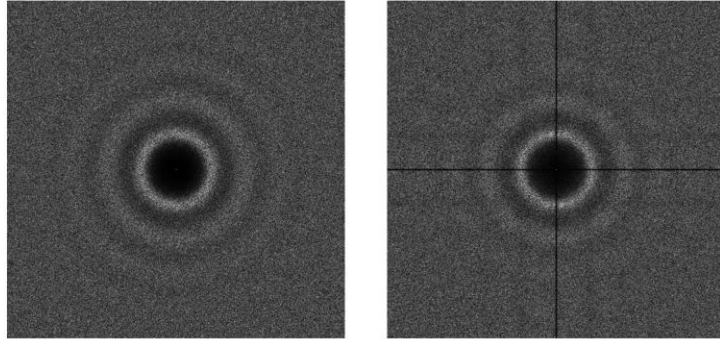


- This is the discrepancy order for point sets, less than sequences.
- Other profiles might be possible, as long as they can stratified.
- Fastest ever! For comparison, AA~Patterns ~100 MPPS, Polyhexes ~10 MPPS.
- Very small, superseded only by penrose tilings. AA~Patterns 64KB

# DISCREPANCY

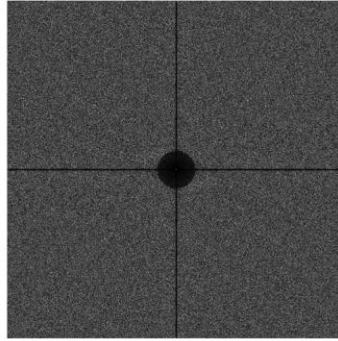
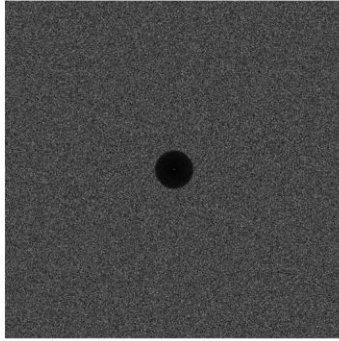


## SPECTRUM: BNOT



- The spectrum is almost identical (provable).
- The crosshair characterizes LD and Latinized point sets.

## SPECTRUM: STEP



## IMAGE SAMPLING (ZONE PLATE)



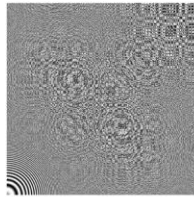
$$\sin(x^2 + y^2)$$

1 Sample per pixel

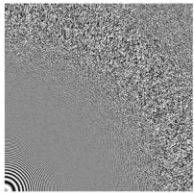
Mitchell Filter



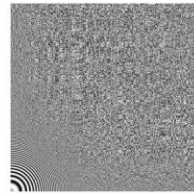
Ground Truth



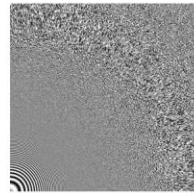
Sobol



BNOT



Scrambled Sobol



LDBN



## CODING COMPLEXITY



```
void generate(int n) {
    double inv = 1.0 / n;
    unsigned mask = t - 1;
    unsigned shift = log2(t);
    int i = 0;
    for (unsigned Y = 0; Y < n; Y++) {
        for (unsigned X = 0; X < n; X++) {
            unsigned index = ((Y & mask) << shift) + (X & mask);
            double x = phi( (Y & 0xffffffff) + (lut[index] & 0xf) );
            double y = phi( (X & 0xffffffff) + (lut[index] >> 4) );
            s[i].x = inv * (X + x);
            s[i++].y = inv * (Y + y);
        }
    }
}
```



## WEBSITE

-  <http://graphics.uni-konstanz.de/publikationen/Ahmed2016LowdiscrepancyBue/index.html>
-  <http://liris.cnrs.fr/ldbn/>
-  Rigorous comparisons
-  Interactive demo
-  Source code

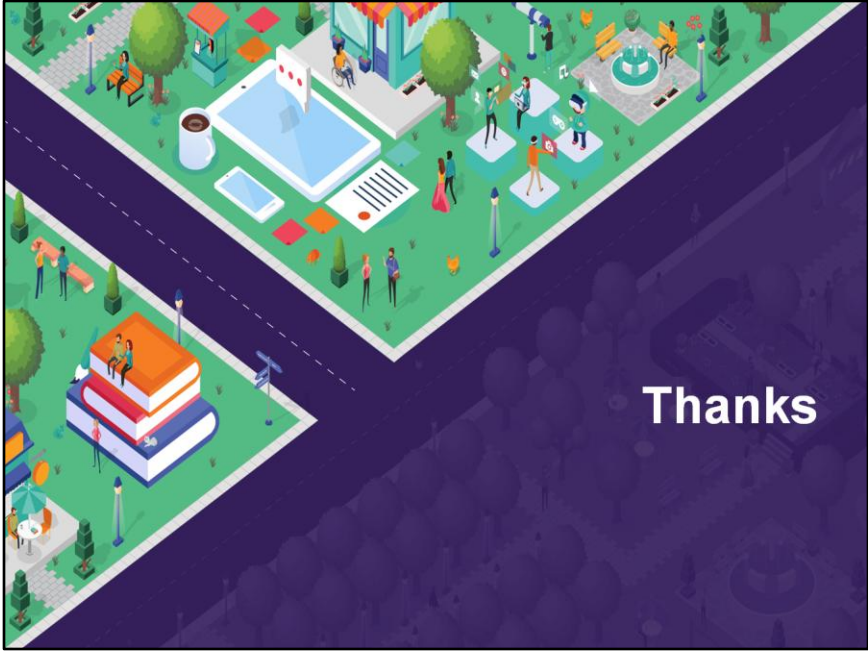


- Website is mirrored in University of Konstanz and University of Lyon.
- You'll find very rigorous comparisons made by my colleague Helene.



## LIMITATIONS

- No adaptivity
- Only 2D
- Reference point set has to be stratified



Thanks