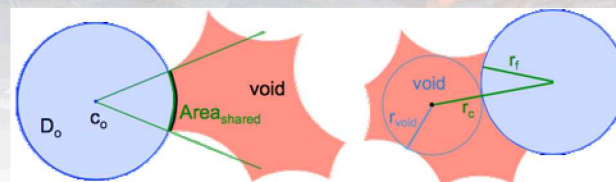
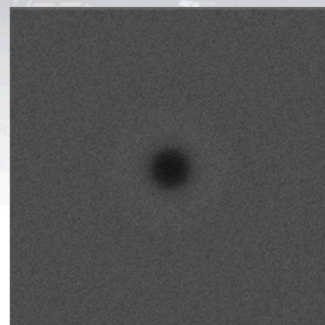
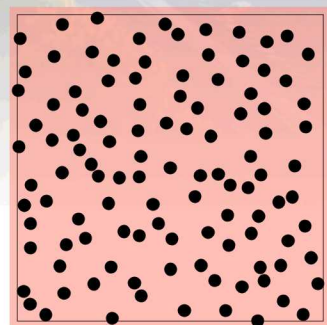
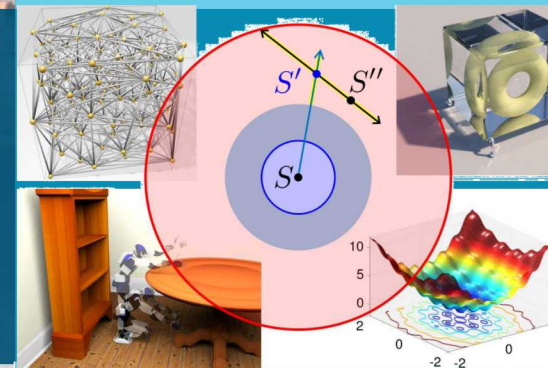


Spoke-Darts for High-Dimensional Blue-Noise Sampling



$$m = \lceil (-\ln \epsilon)(\beta^* - 1)^{1-d} \rceil \Leftrightarrow \beta^* = 1 + \left(\frac{-\ln \epsilon}{m} \right)^{1/(d-1)}$$

PRESENTED BY

Scott A. Mitchell

ACM TOG 37:2, May 2018

Scott A. Mitchell, Mohamed S. Ebeida, Muhammad A. Awad, Chonhyon Park, Anjul Patney, Ahmad A. Rushdi, Laura P. Swiler, Dinesh Manocha (now UMD), Li-Yi Wei

SIGGRAPH 2018
18 minutes talk
15 Aug 10:45 am session talk 4
West Building, Room 109-110



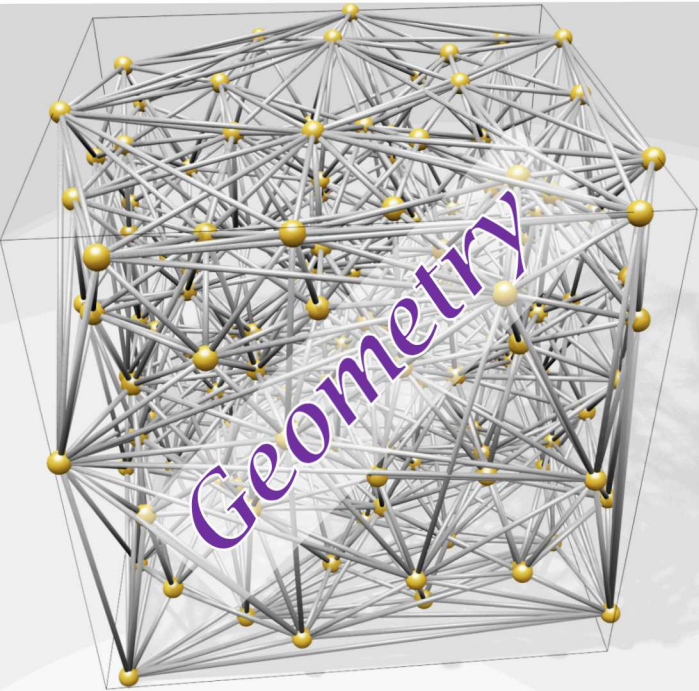
NVIDIA



UC DAVIS
UNIVERSITY OF CALIFORNIA



Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.



Geometry

Motivation

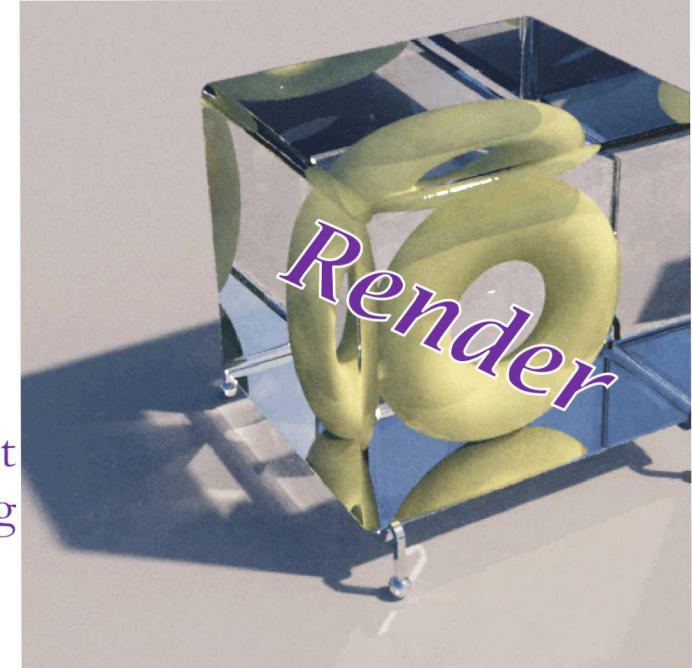
High-dimensional

blue-noise sampling is useful
but hard to generate

8-100D: approximate
Delaunay Graphs
(Voronoi neighbors)

8D: proof-of-concept
path tracing

Social proof of utility:
Bridson SIGGRAPH 2007
cited 200 times



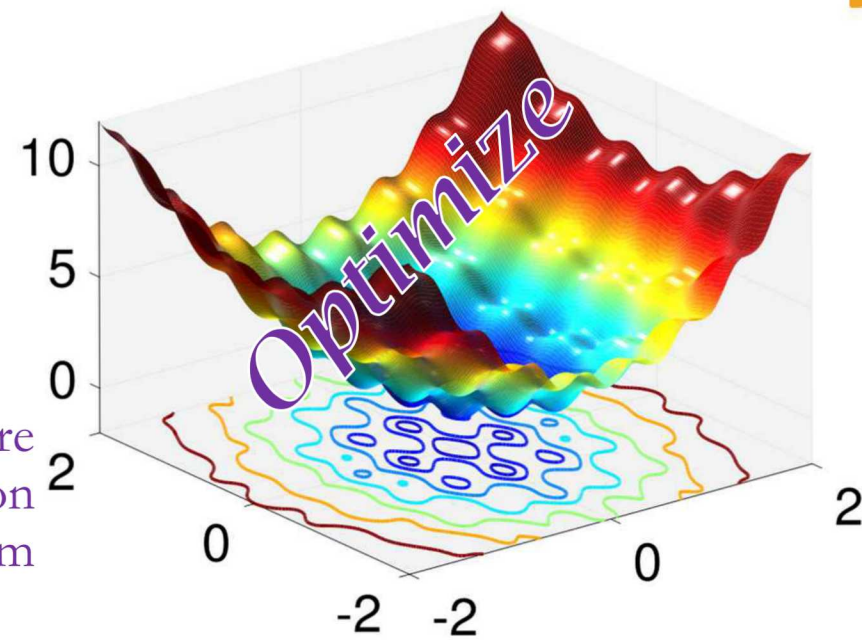
Render



Motion
Plan

23D: find a path in
robot configuration space

100D: adaptively explore
black-box function
to find global minimum



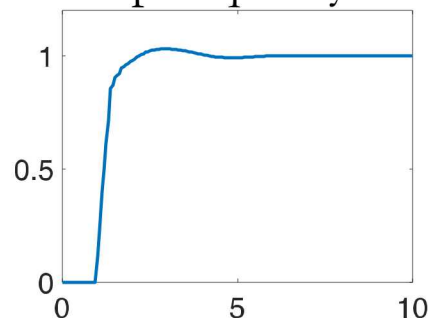
Optimize

Motivation

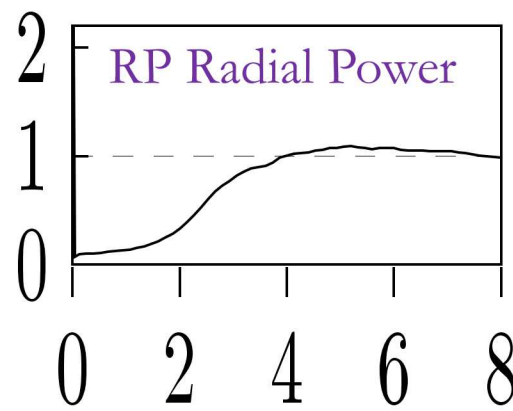
Goal: algorithm to produce point distributions

Requirements

- ✓ Output: blue-noise, uniform-random except
 - ✓ No points too close
 - ✓ No big gaps
- ✓ Algorithm
 - ✓ Memory & time scales to high dimensions (e.g. 20D)
 - ✓ Locally adaptive, general domain shapes
- ✓ Confidence: provable output quality

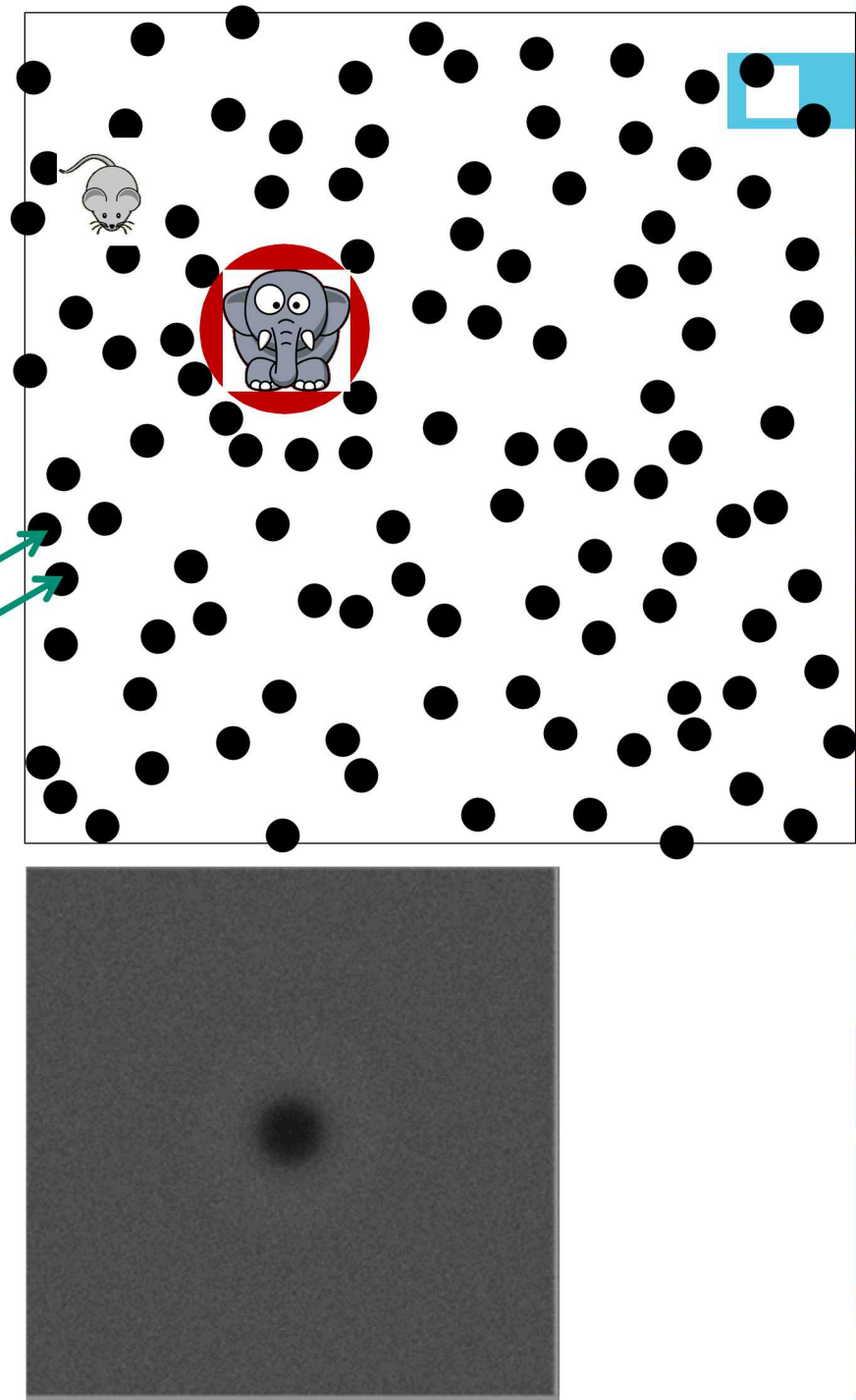


RDF Radial Distance Function



Maximum
domain-to-sample
distance

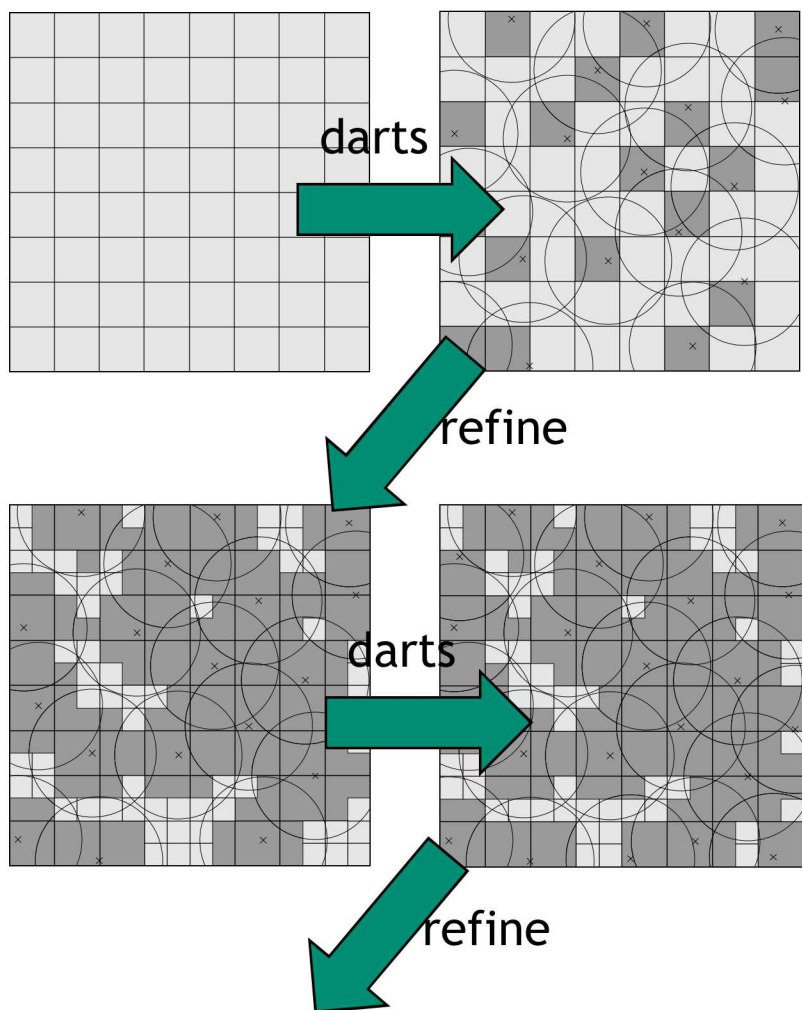
Minimum
sample
separation



What's wrong with the algorithms we already have?

SimpleMPS guarantees saturation

$$\text{runtime \& memory} = O(n)$$

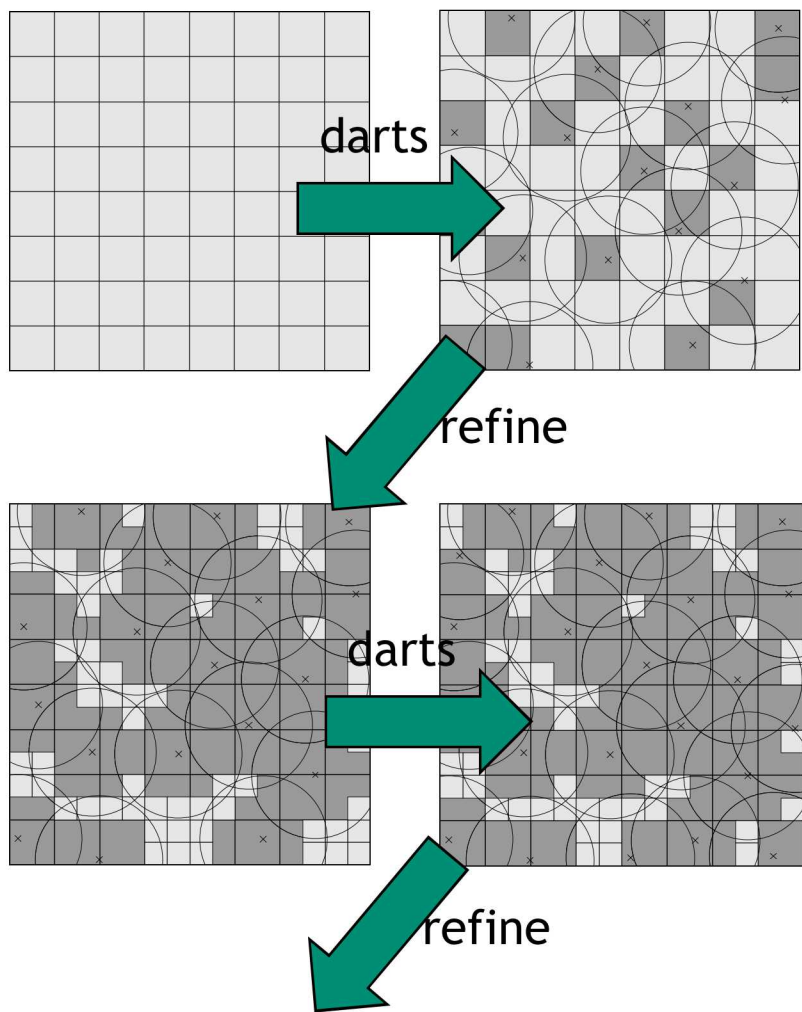


```
divide domain into cubes
while  $\exists$  cubes, and cube diagonal > machine precision
do  $(A(d) \times \# \text{cubes})$  times:
    pick a cube
    pick sample from cube
    if distance(sample, prior samples) > r
        accept sample
        discard cube
    refine cubes
    discard covered cubes
```

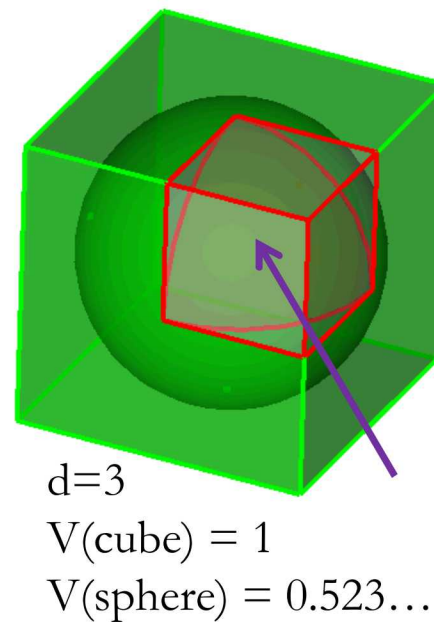
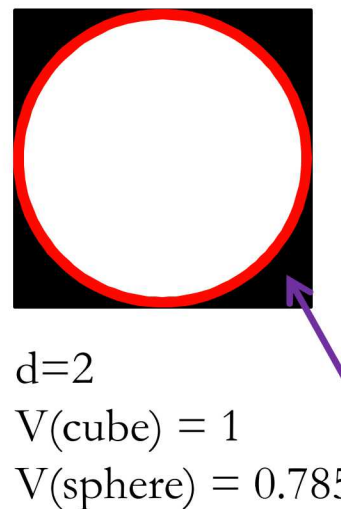
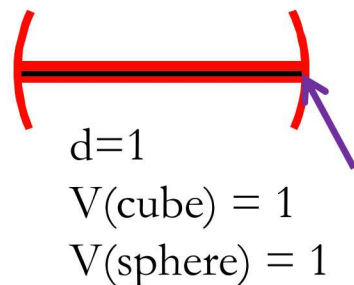

What's wrong with the algorithms we already have?

SimpleMPS guarantees saturation ... but doesn't scale by dimension, d . ☹

$$\text{runtime \& memory} = O(nd^{d/2})$$



Problem: cube poorly approximates sphere
Exponentially worse as dimension increases
More empty boxes, memory limit $d \approx 6$



...

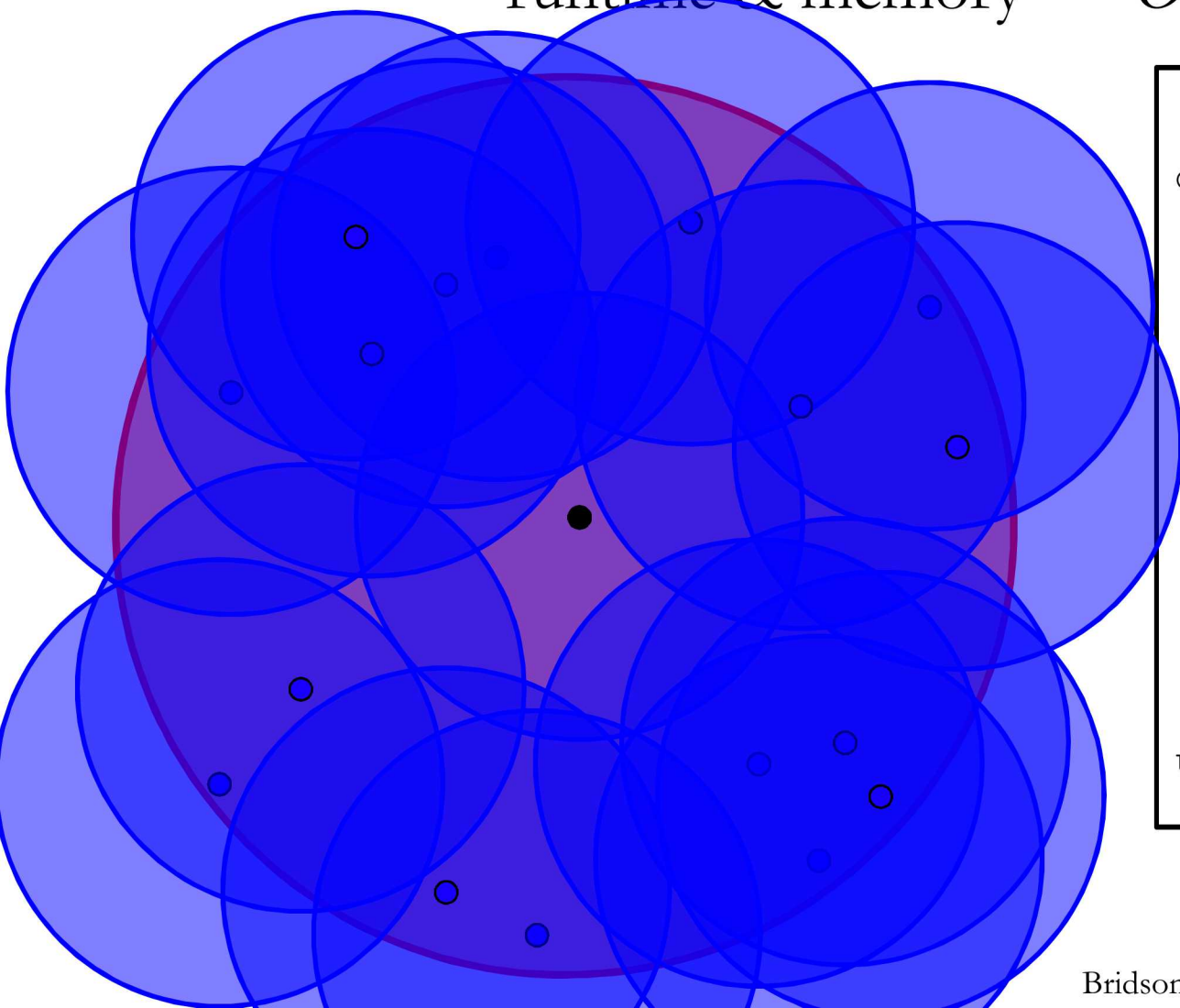
$d \rightarrow \infty$
 $V(c) = 1$
 $V(s) \rightarrow 0$

Any algorithm that constructs (an approximation of) remaining sample space is doomed to be exponential-in- d

What's wrong with the algorithms we already have?

Bridson 2007* scales

$$\text{runtime \& memory} = O(dn^2)$$



Bridson 2007* pseudocode

```
do
  prior = randomly pop Front
  do
    pick sample from volume of
      (r,2r) annulus of prior
    if distance(sample, all samples) > r
      accept sample
      add sample to Front
  until 30 consecutive rejections
until Front is empty
```

30+ depending
on dimension

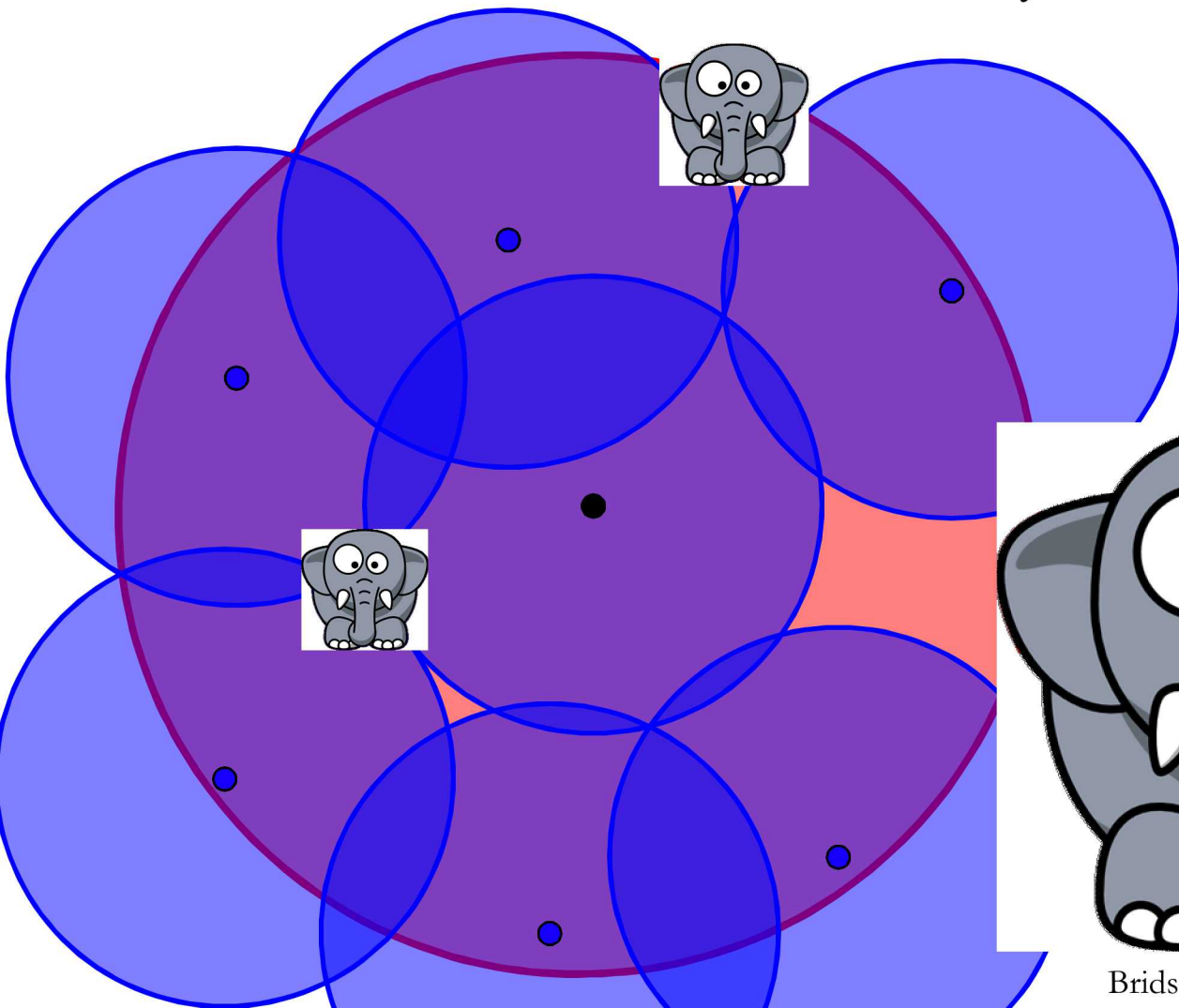
*Modified: no background grid, no exponential-in-d complexity.

Bridson 2007, "Fast Poisson disk sampling in arbitrary dimensions." SIGGRAPH '07 sketch.

What's wrong with the algorithms we already have?

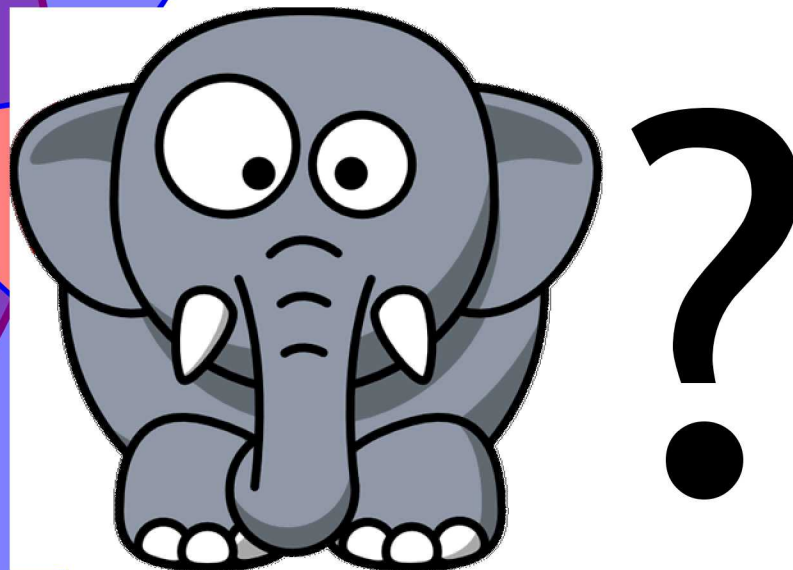
Bridson 2007* scales ... but doesn't guarantee saturation ☹

$$\text{runtime \& memory} = O(dn^2)$$



Trivial
in one annulus

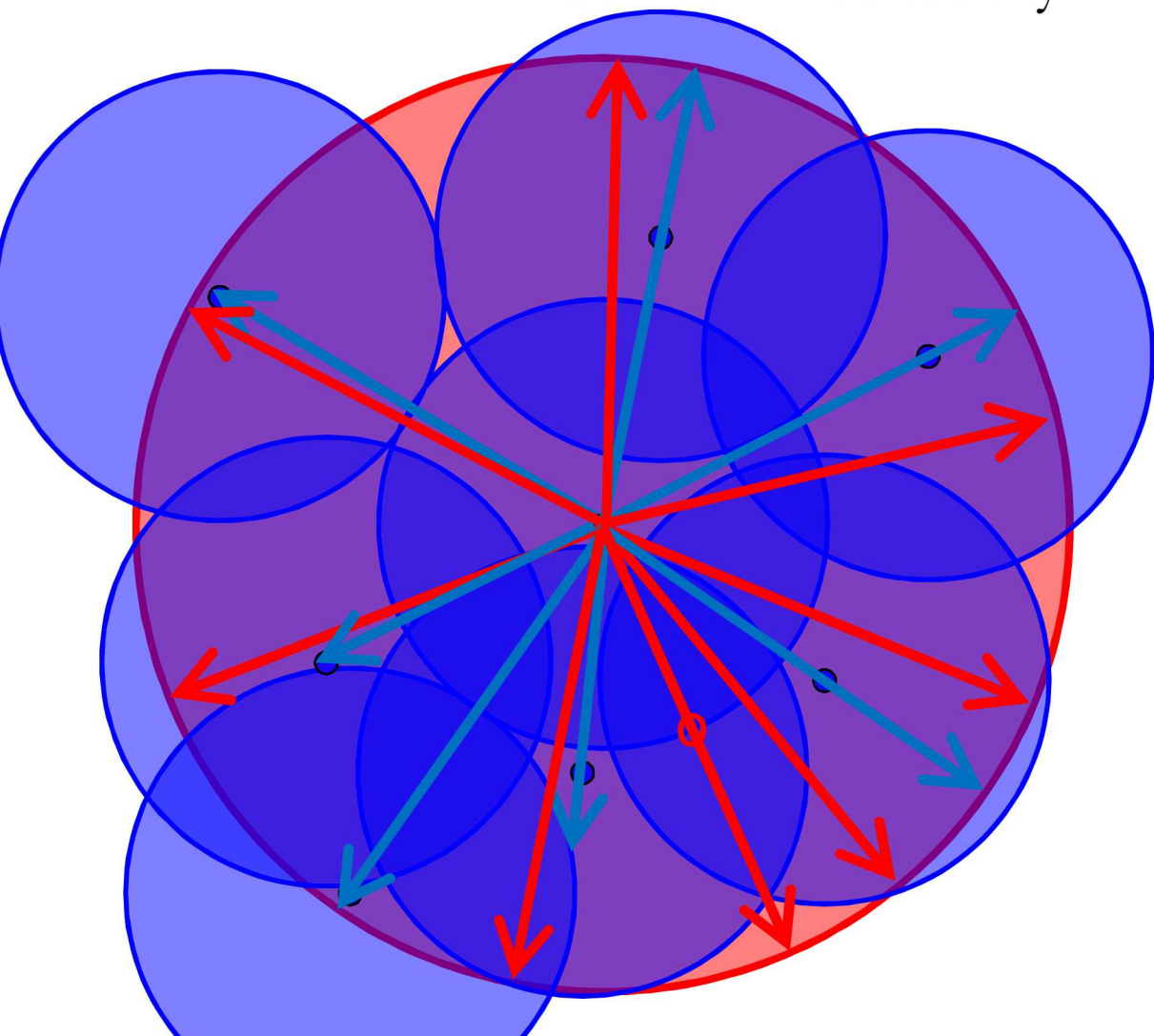
Unknown
outside all annuli?



Proposed Spoke-Darts algorithm

Spoke-Darts scales

$$\text{runtime \& memory} = O(dn^2)$$



Spoke-Darts
mod from Bridson

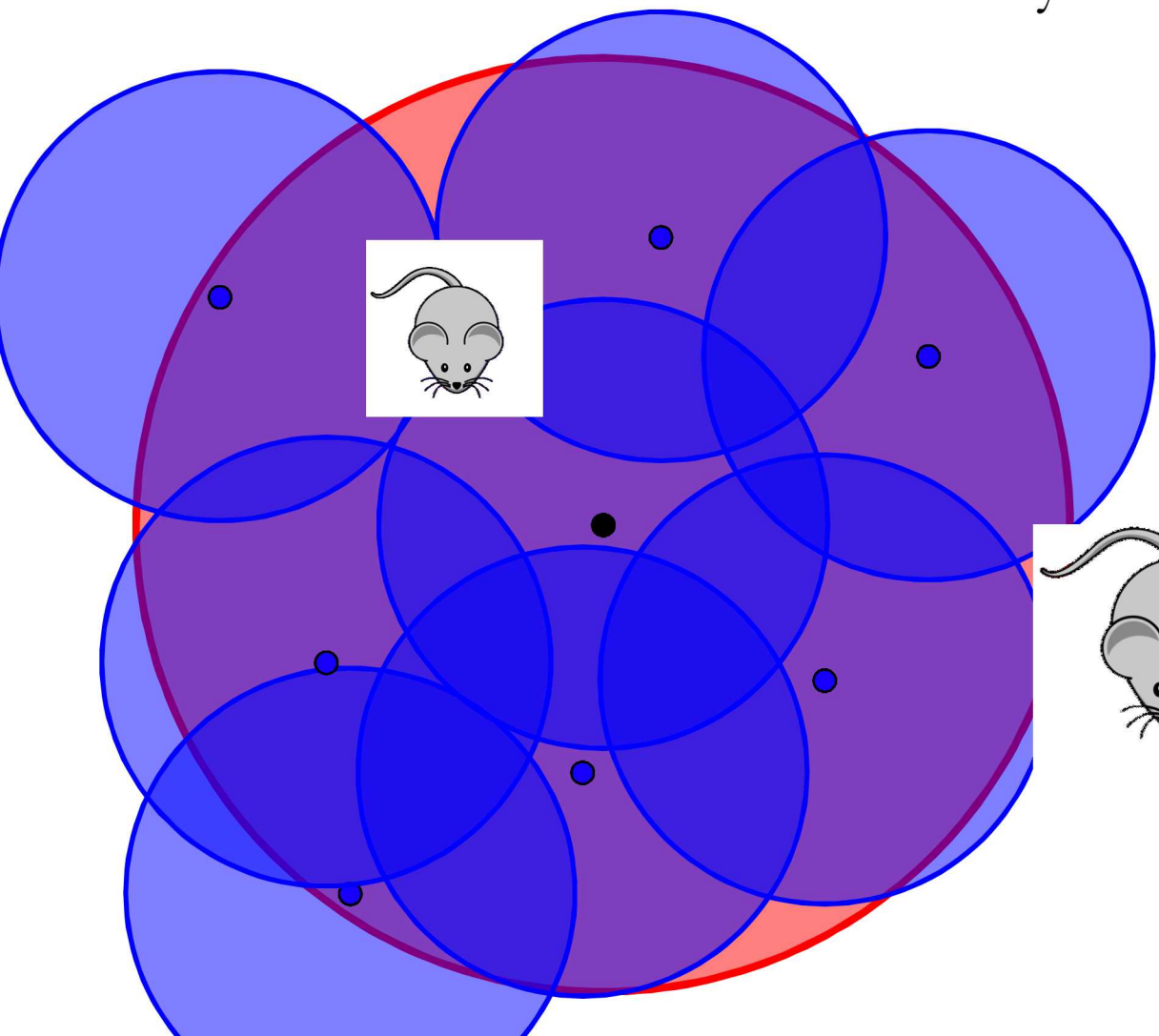
```
do
  prior = randomly pop Front
  do
    pick sample from radial line through
      (r,2r) annulus of prior
    if distance(sample, all samples) > r
      accept sample
      add sample to Front
  until 12 consecutive rejections
until Front is empty
```

12 same for all
dimensions

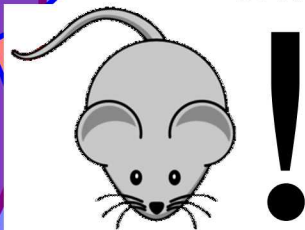
9 Proposed Spoke-Darts algorithm

Spoke-Darts scales ... and guarantees saturation 😊

runtime & memory = $O(dn^2)$

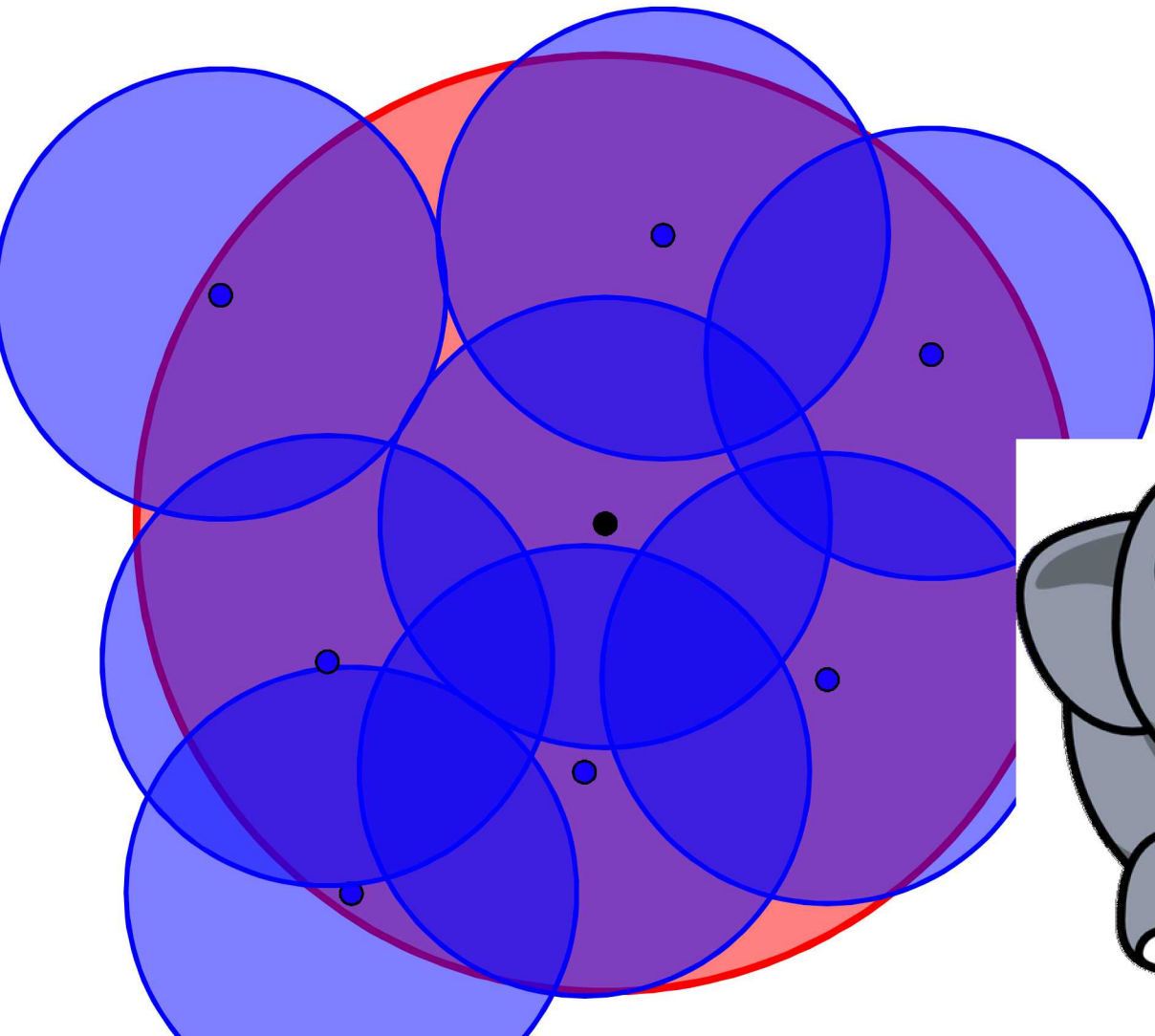


Proved
probabilistic bound
outside all annuli!

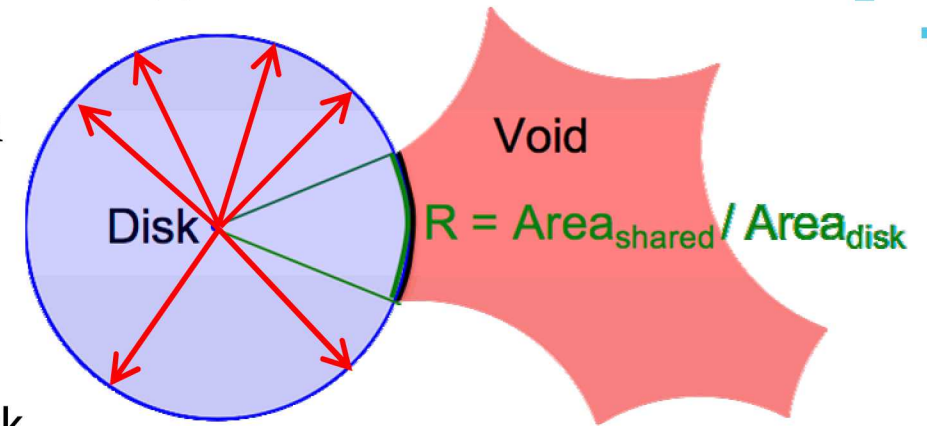


Proof of saturation

Spoke-Darts scales ... and guarantees saturation



Suppose there exists a void



One disk

Missed 12 times, so area R is probably small,

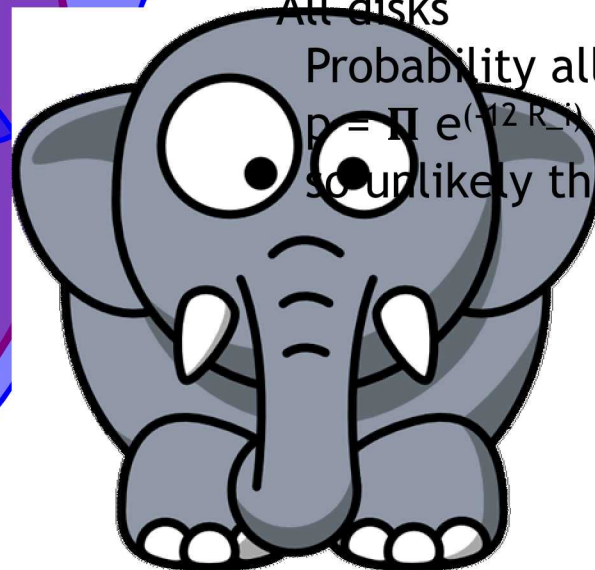
Probability of 12 misses = $\prod (1-R) = (1-R)^{12} < e^{(-12R)}$

All disks

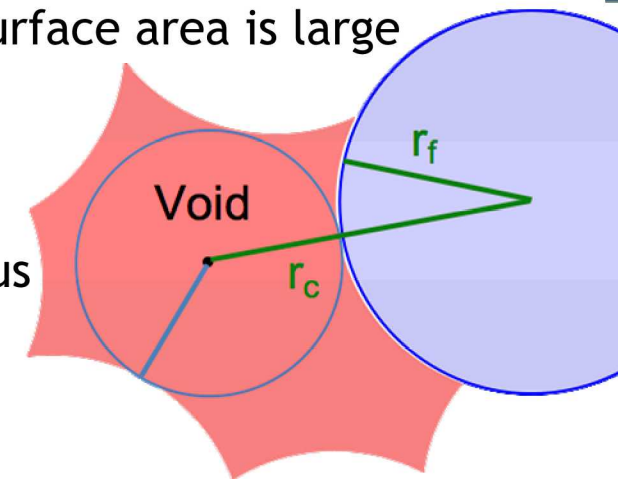
Probability all missed = product of probabilities

$$p = \prod e^{(-12 R_i)} = e^{-12 \sum R_i}$$

so unlikely that the total surface area is large



all void radius



Structure of saturation guarantee

$$m = \lceil (-\ln \epsilon)(\beta^* - 1)^{1-d} \rceil$$

$$\beta^* = 1 + \left(\frac{-\ln \epsilon}{m} \right)^{1/(d-1)}$$

where

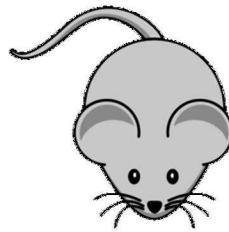
$$\beta^* = r_c / r_f$$

ϵ = chance beta exceeded

m = #misses, failed darts

d = dimension

pick any three



Magic values for dimensional independence

$$\frac{-\ln \epsilon}{m} = 1 \implies \beta^* = 2 \forall d$$

e.g.

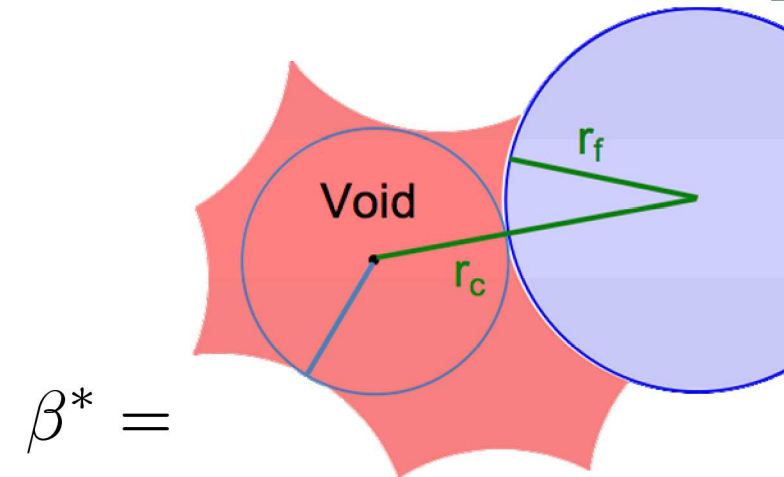
$$m = 12$$

$$\implies \epsilon = 10^{-5}$$

probability $1 - 10^{-5}$

that $\beta^* < 2 \forall d$

e.g. $m = 14 \implies \epsilon = 10^{-6}$
 $m = 30 \implies \epsilon = 10^{-13}$



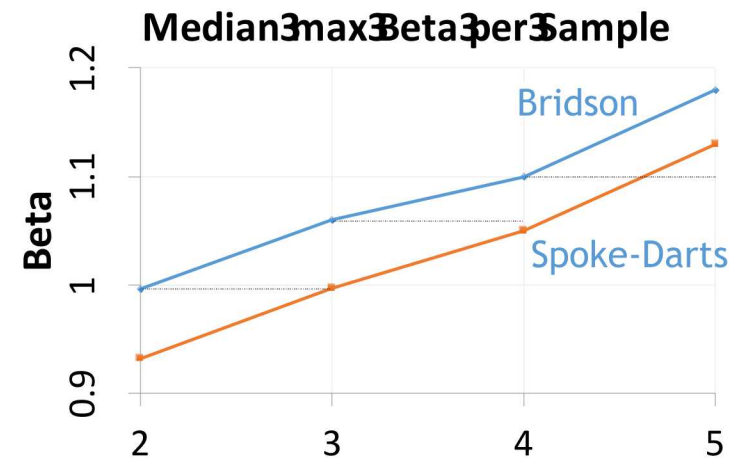
Output Saturation in Practice = better than Bridson

one dimension “for free”

Theory: $\beta = \text{constant}$

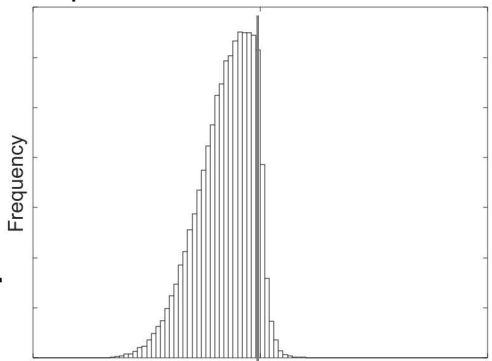
Practice: β increases and narrows with d

- Narrowing consistent with theory

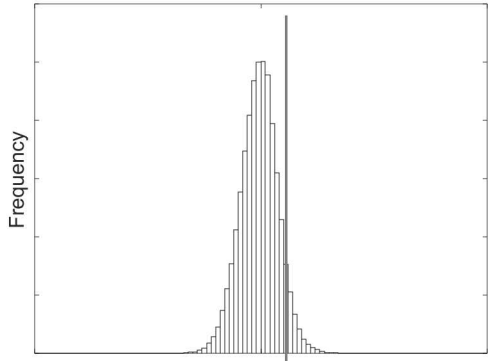


Spoke-Darts

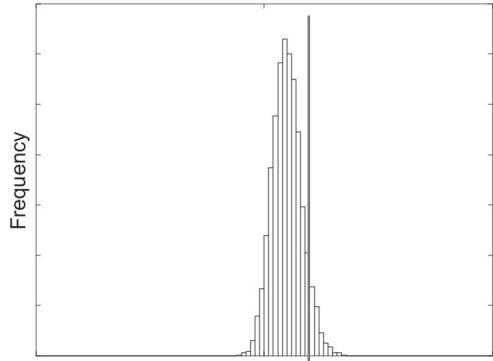
Sample to its Farthest Voronoi Vertex Distance



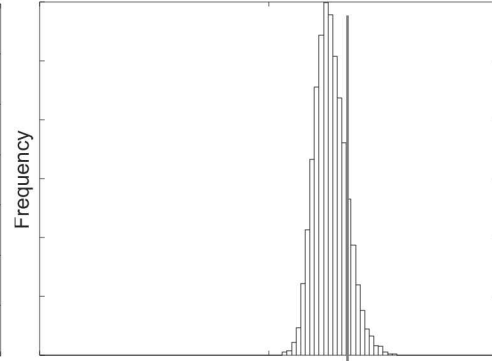
Sample to its Farthest Voronoi Vertex Distance



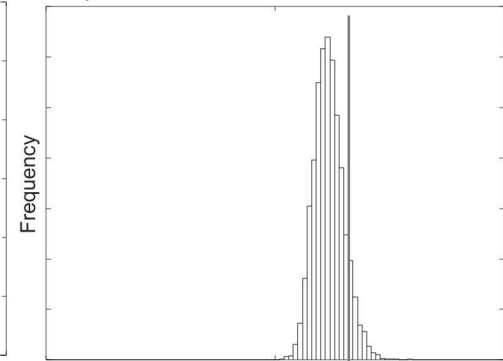
Sample to its Farthest Voronoi Vertex Distance



Sample to its Farthest Voronoi Vertex Distance



Sample to its Farthest Voronoi Vertex Distance



dimension = 2

3

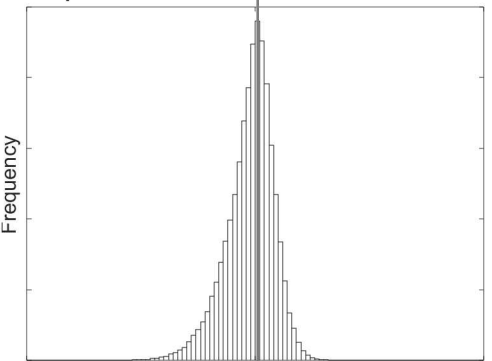
4

5

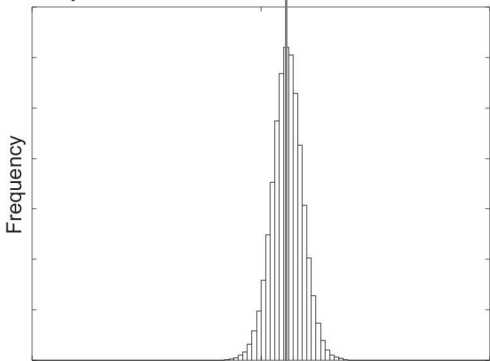
6

Bridson

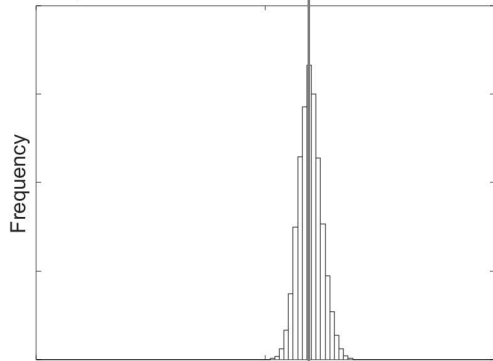
Sample to its Farthest Voronoi Vertex Distance



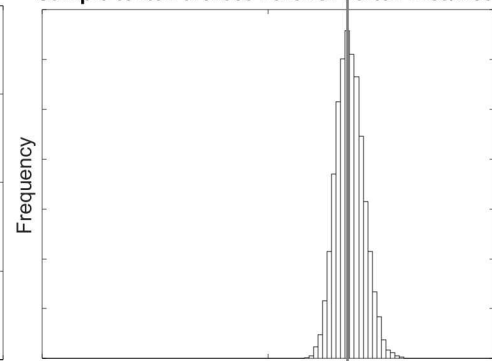
Sample to its Farthest Voronoi Vertex Distance



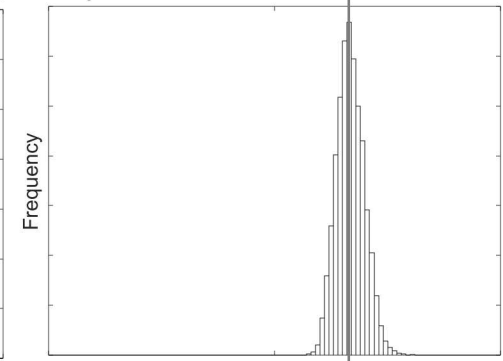
Sample to its Farthest Voronoi Vertex Distance



Sample to its Farthest Voronoi Vertex Distance



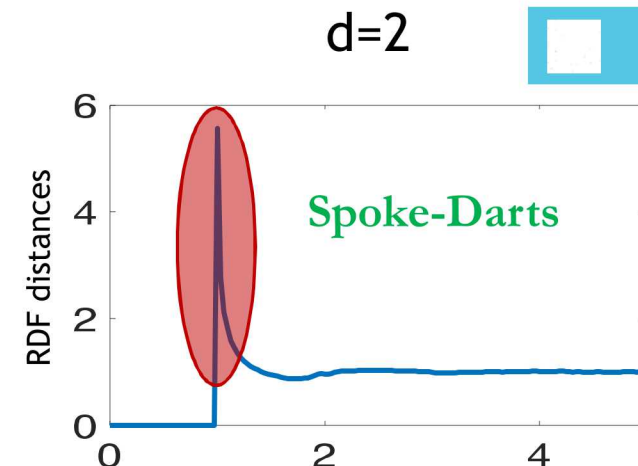
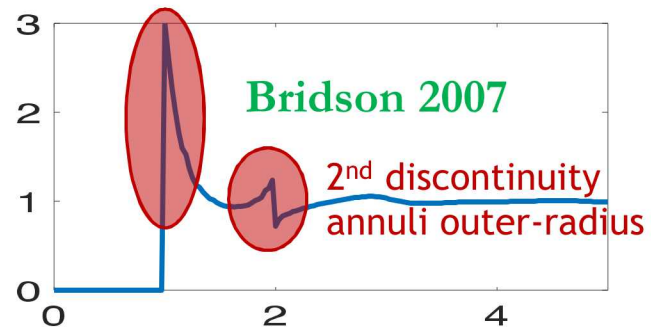
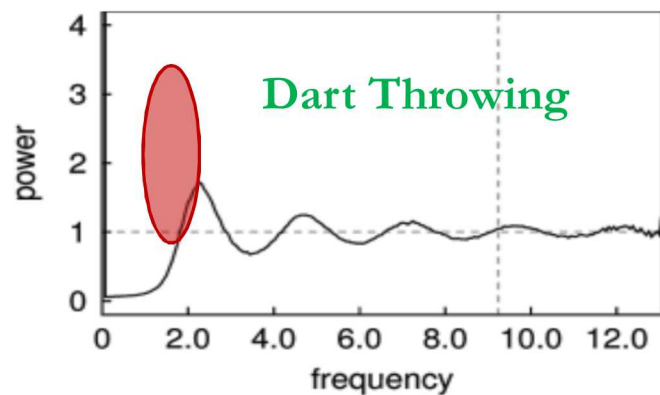
Sample to its Farthest Voronoi Vertex Distance



Output Randomness – Blue noise

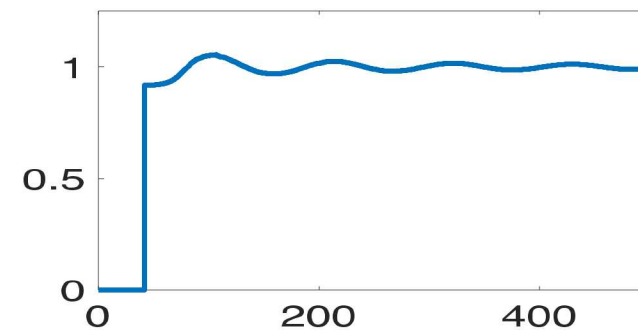
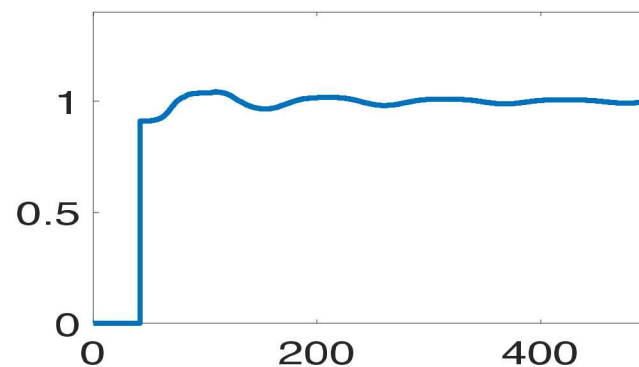
Sharp spike at radius!
(annuli inner-radius)

Pairwise distances
between samples

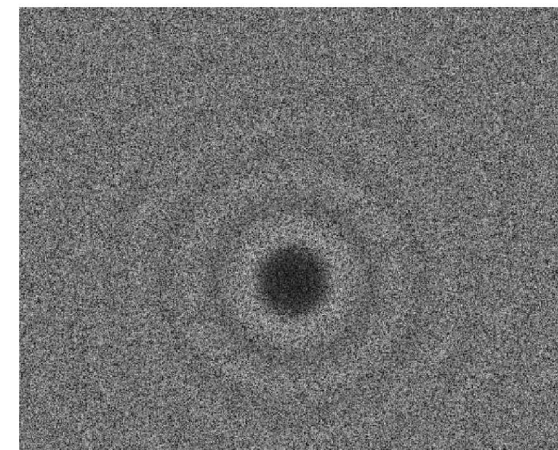
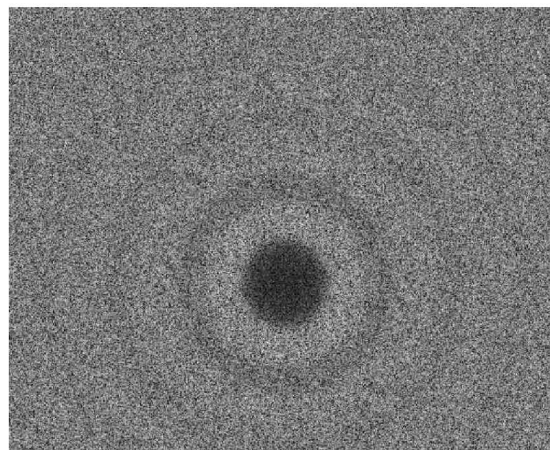


Fourier Transform, 1d
integral over angle by radius

Dart throwing images from
Blue Noise Sampling
with Controlled Aliasing,
TOG 32:3, 2013.



Fourier Transform



Output Randomness – Blue noise

Eliminate spike

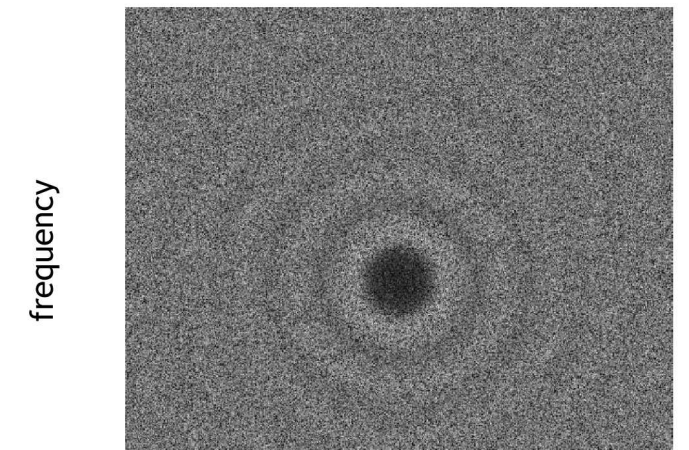
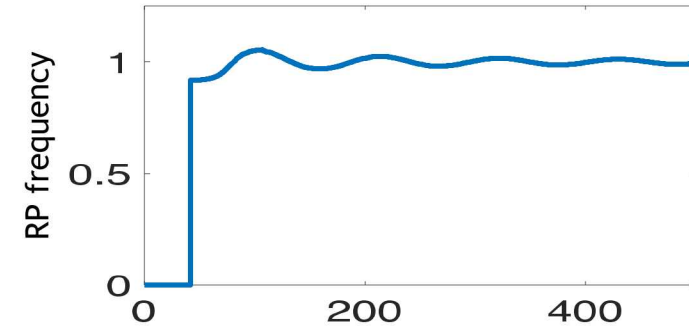
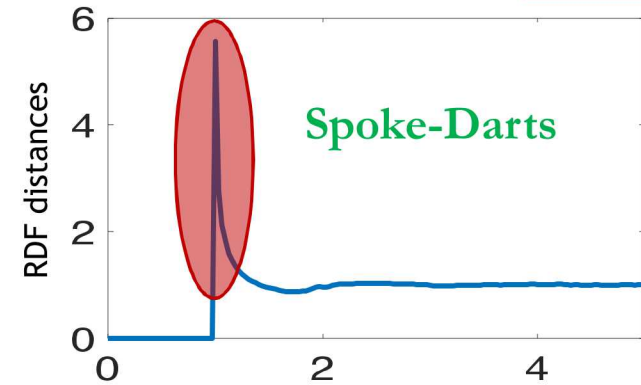
- Post-processing optimization* = expensive, 2d
- Sample non-uniformly
 - By spoke-length? Uniform by swept volume? Worse!
 - Any sharp local rule \rightarrow global discontinuity ☹

Good idea

- r_{cover} max domain-point-to-sample distance
- r_{free} min sample-to-sample distance

Bad idea

- $r_{\text{free}} = r_{\text{cover}} \iff \mathbf{B}=1$
- Traditional goal of Maximal Poisson-disk Sampling!
 - Serves no purpose

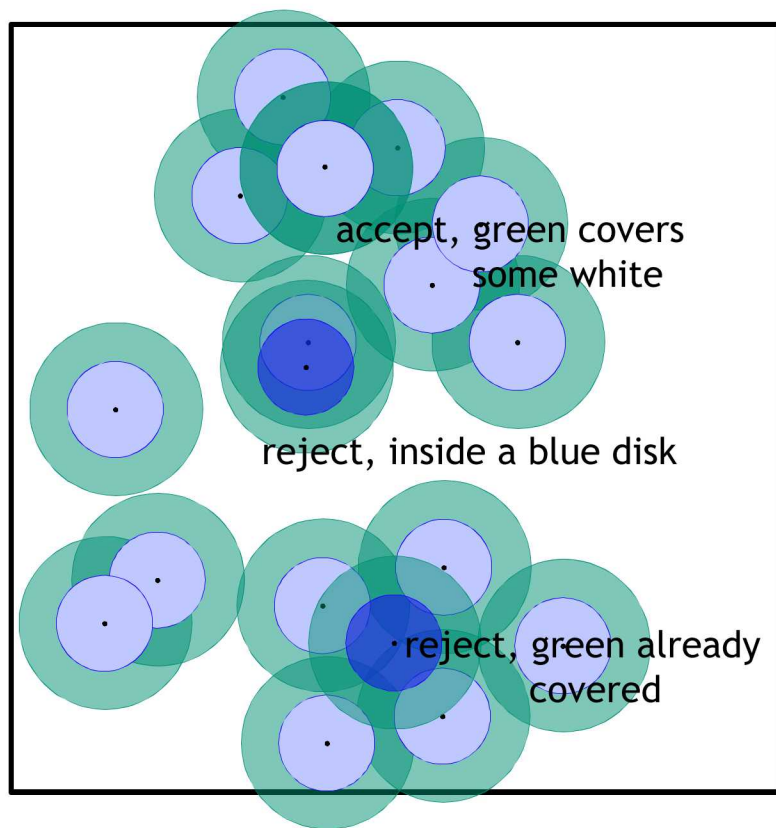


* Blue Noise Sampling with Controlled Aliasing, TOG 32:3, 2013.

Output Randomness – Blue noise

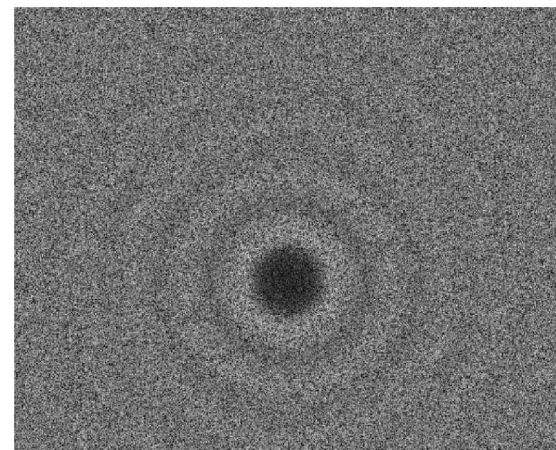
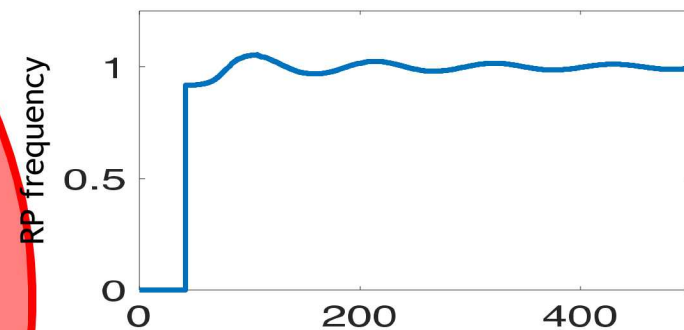
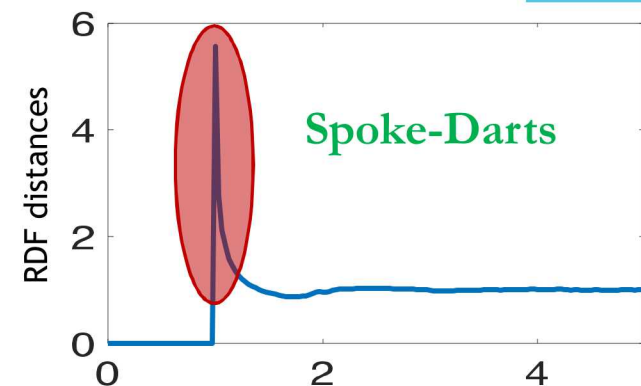
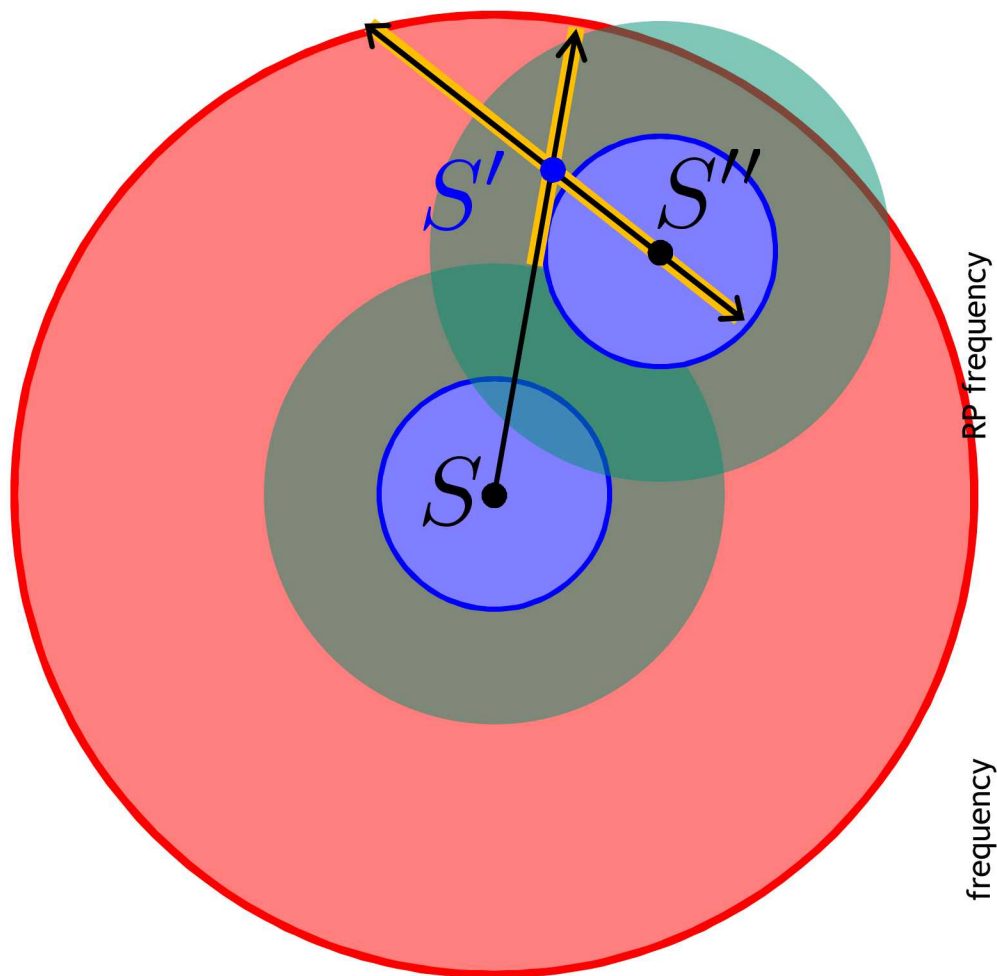
Eliminate spike – we solved in 2012 ☺

- † **Two-radii**: $r_{\text{free}} \neq r_{\text{cover}}$
 - Small blue r_{free} minimum sample separation
 - Large green r_{cover} maximum domain-to-sample
 - Unique coverage: accept only if covers white



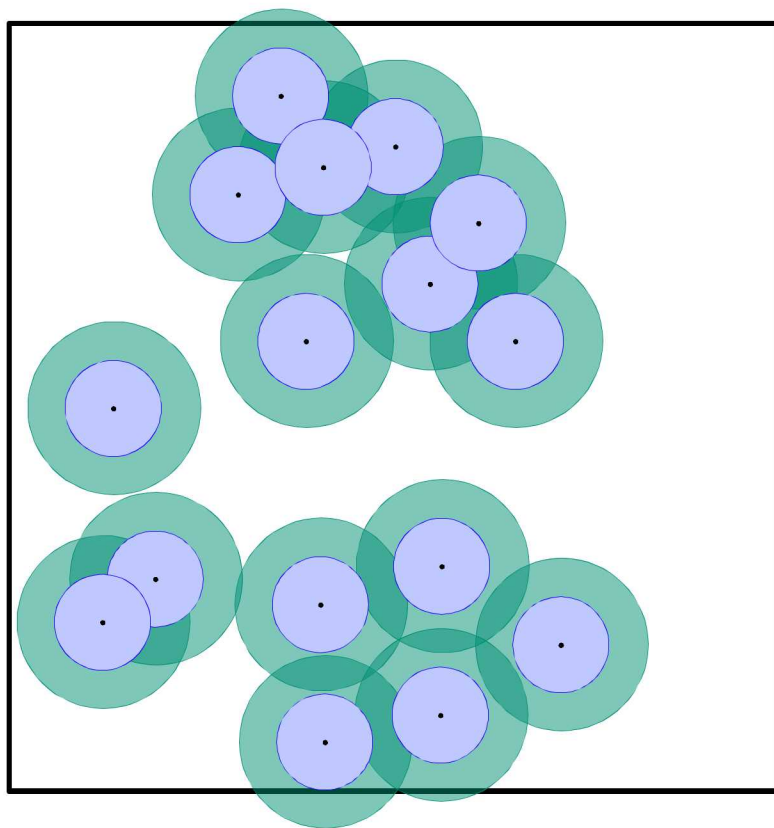
- Two-spokes** mimic Two-radii

- 1st spoke, trim by large green
- 2nd spoke, trim by small blue



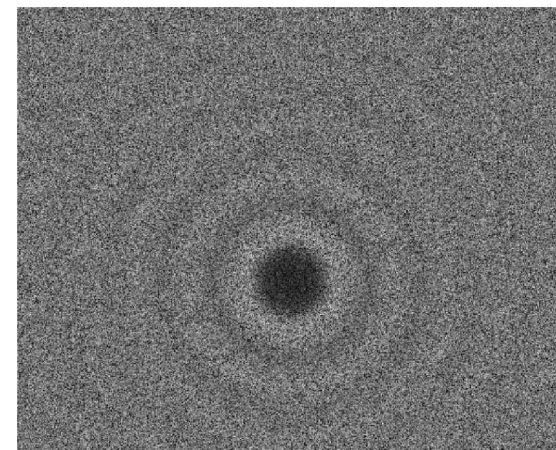
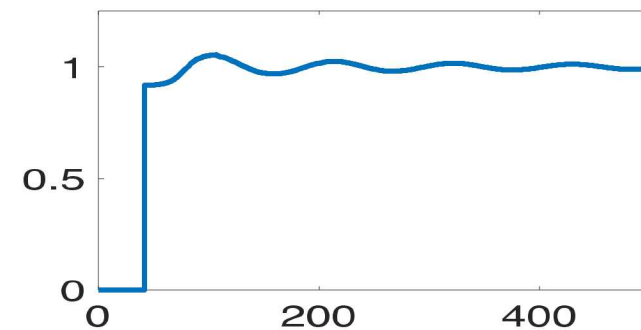
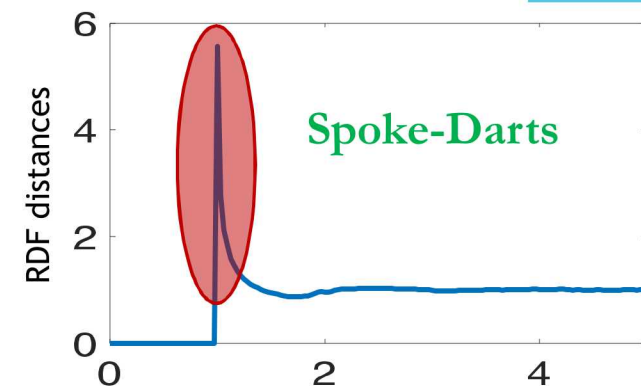
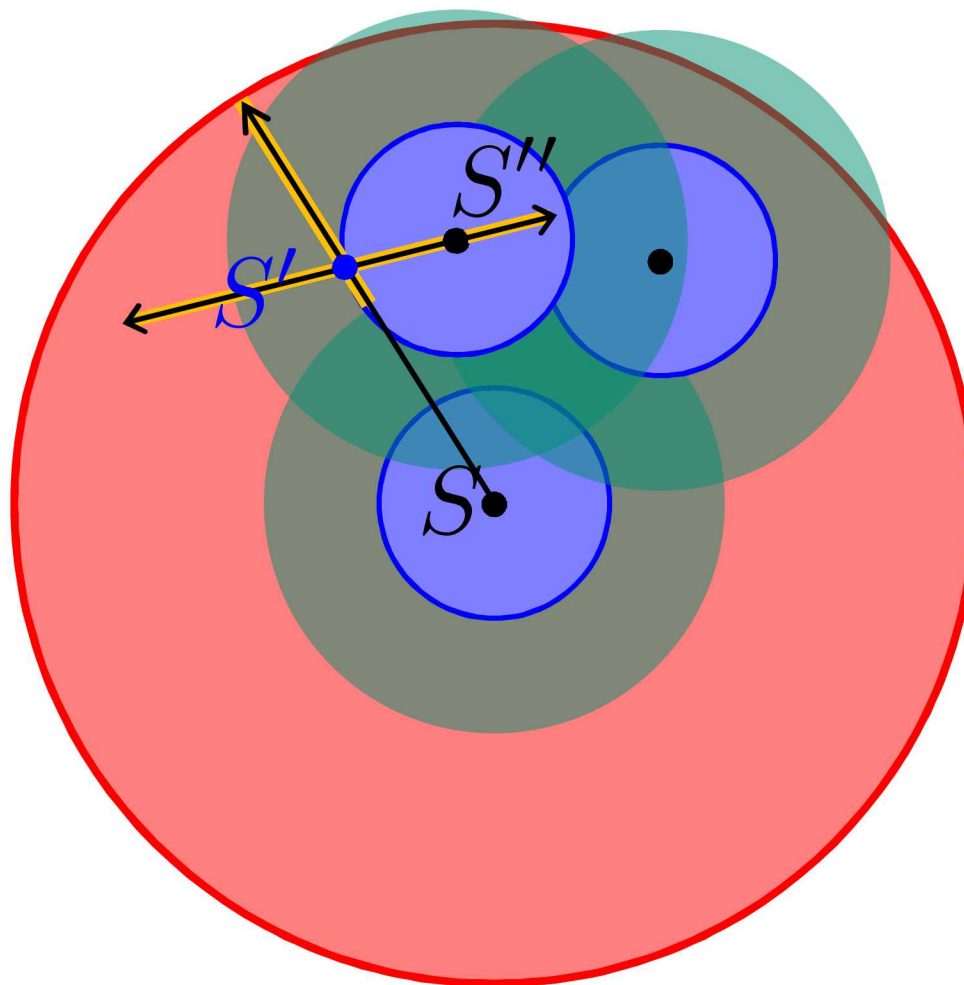
Eliminate spike

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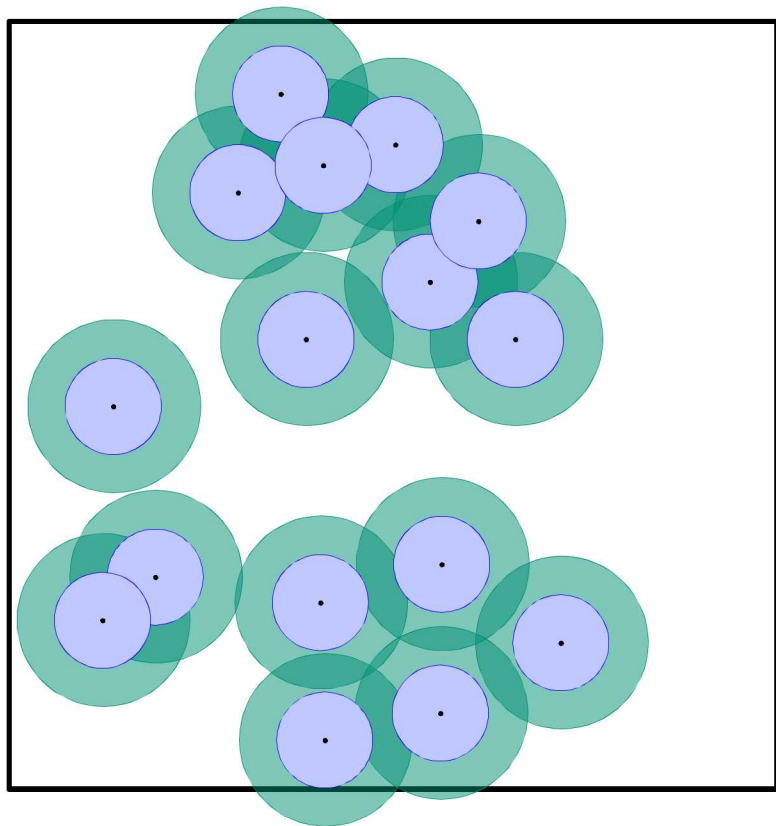
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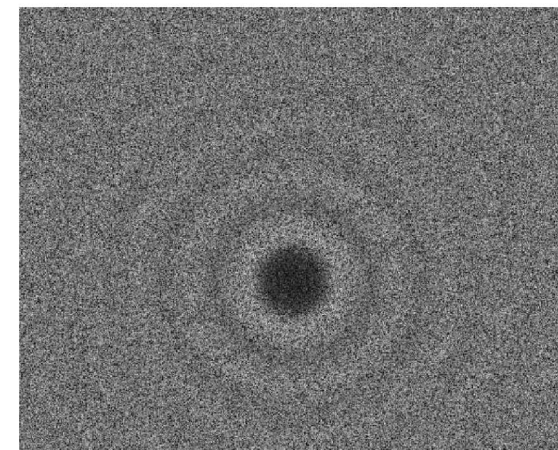
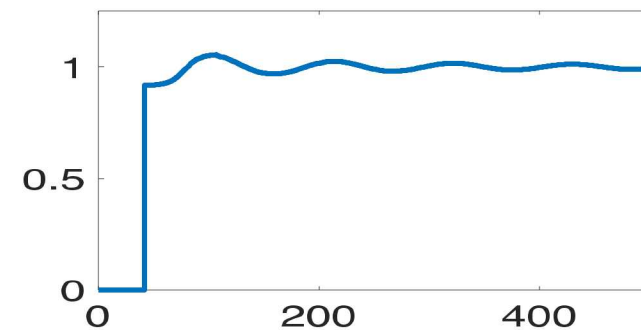
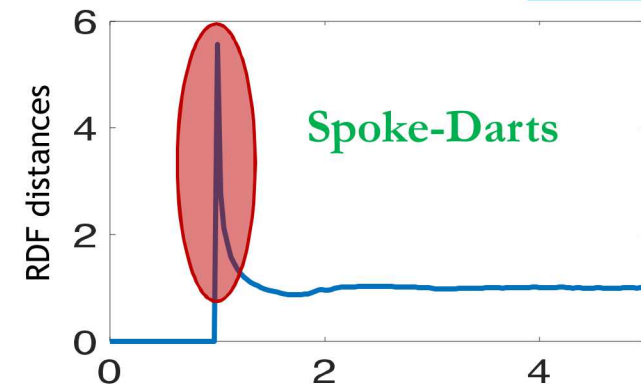
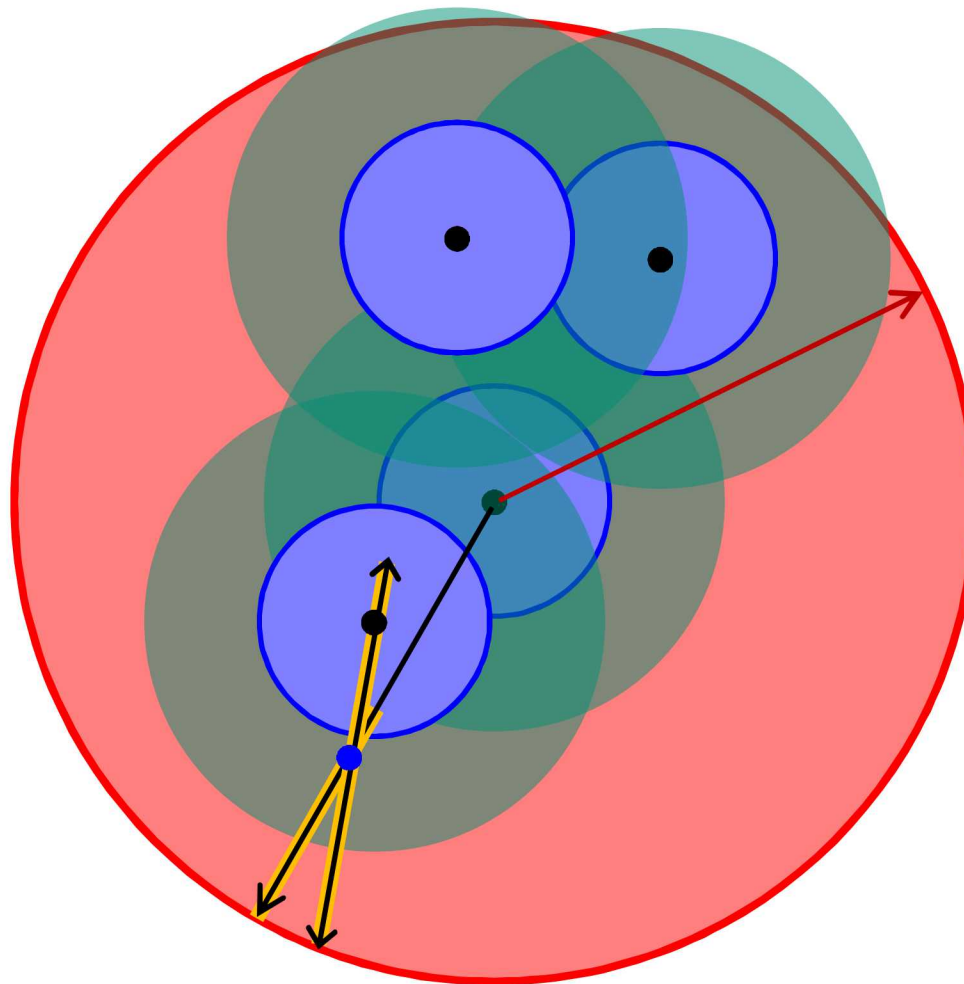


Eliminate spike

- † **Two-radii**: $r_{\text{free}} \neq r_{\text{cover}}$
 - Small blue r_{free} minimum sample separation
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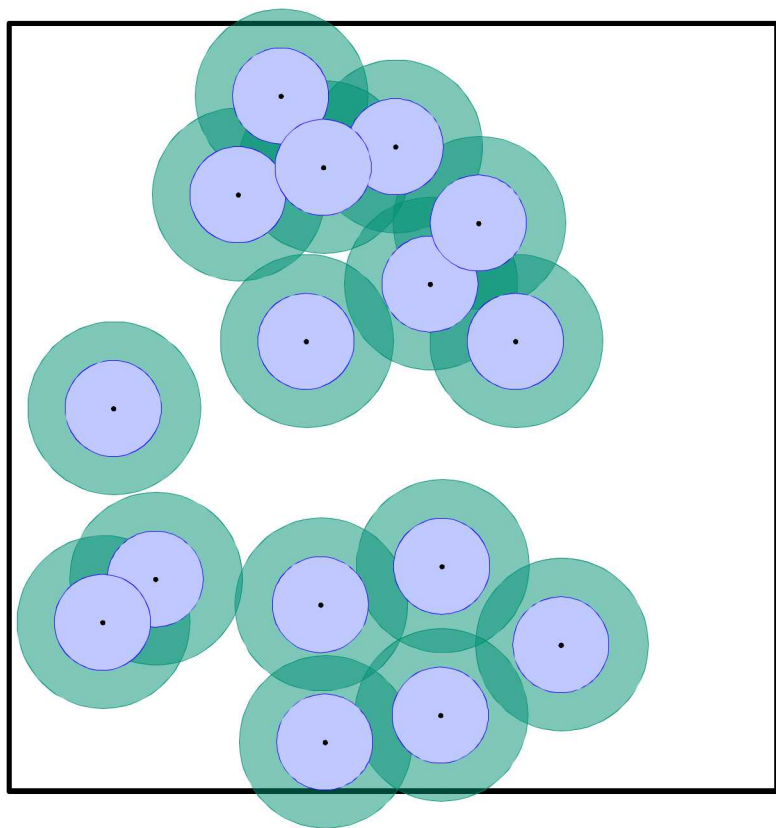


- Two-spokes** mimic Two-radii
 - 1st spoke, trim by large green
 - 2nd spoke, trim by small blue



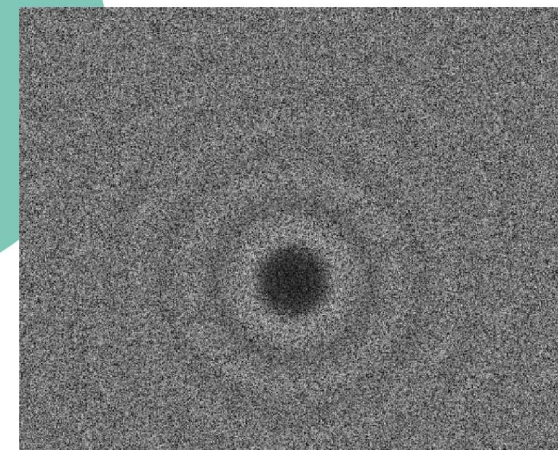
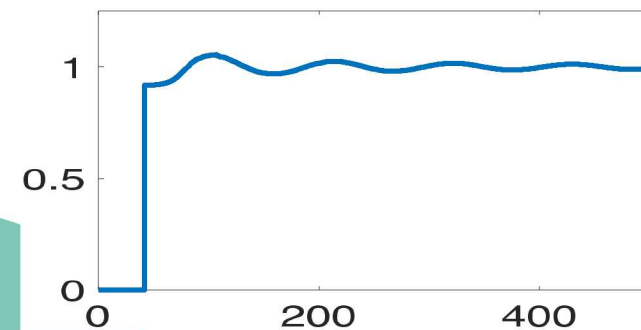
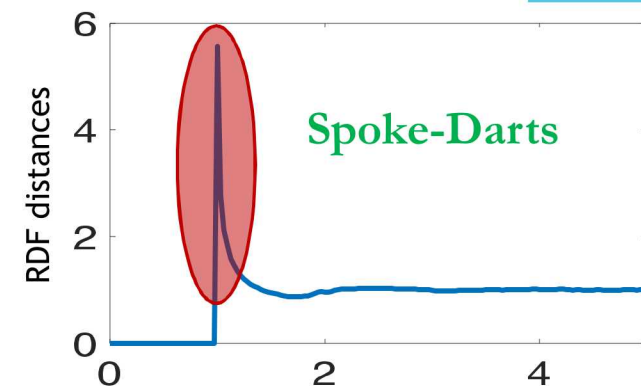
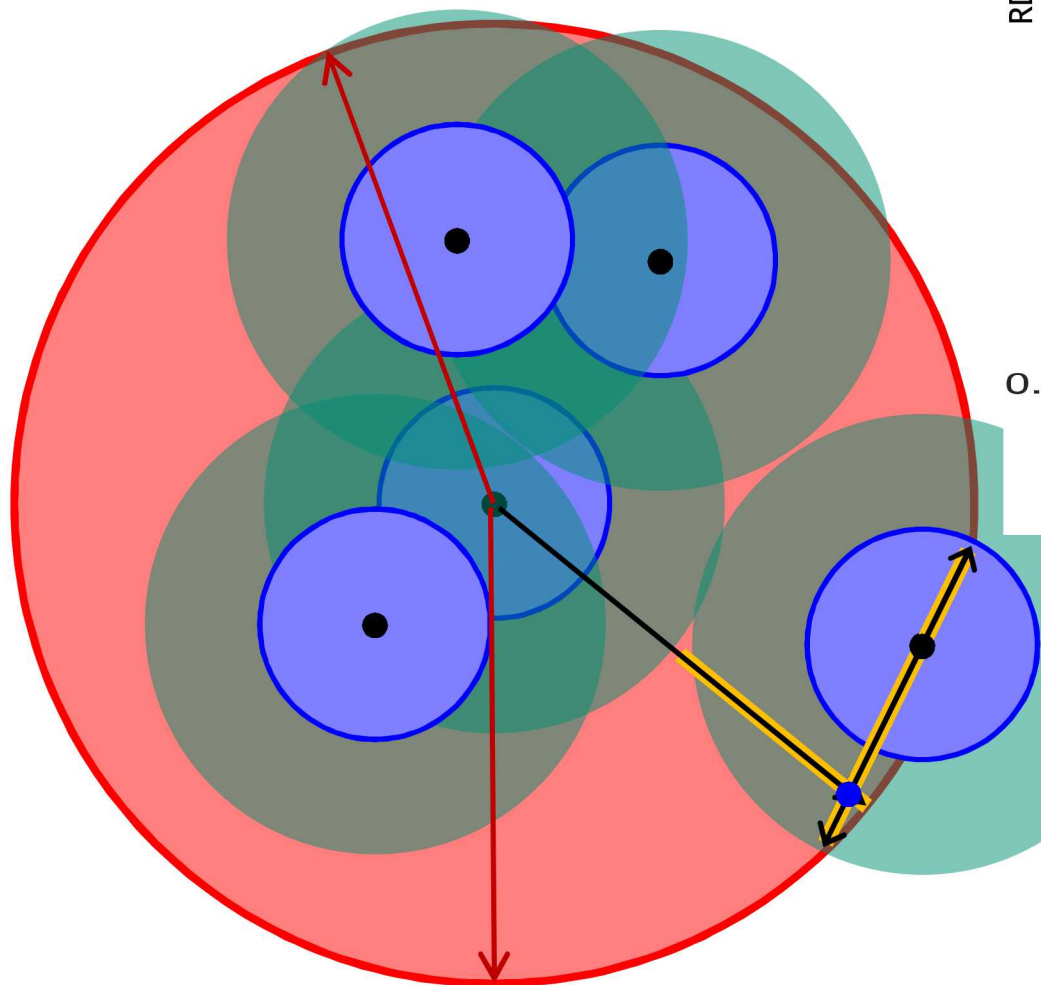
Eliminate spike

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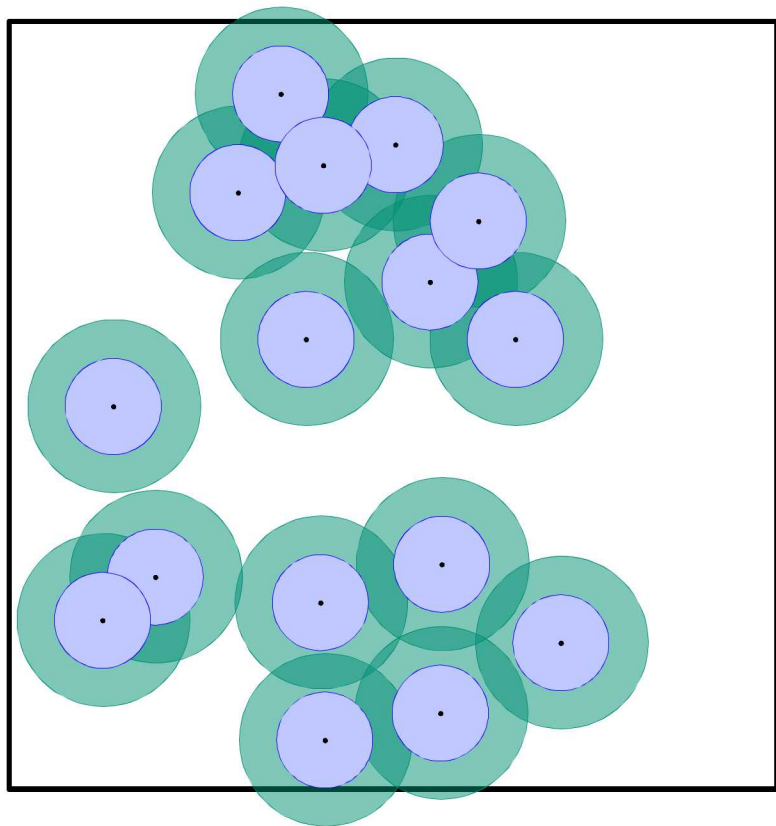
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- 2nd spoke, trim by small blue

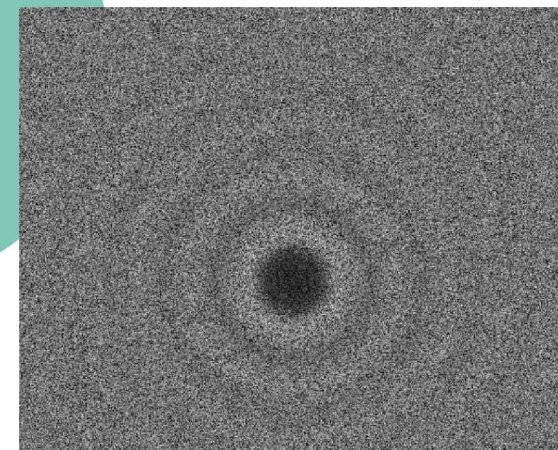
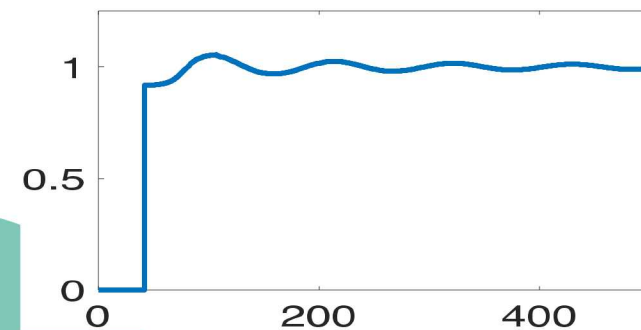
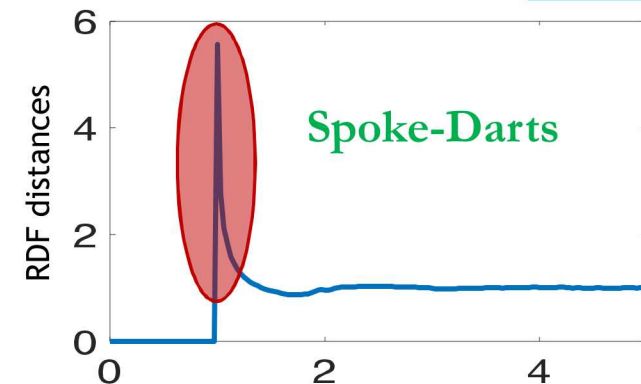
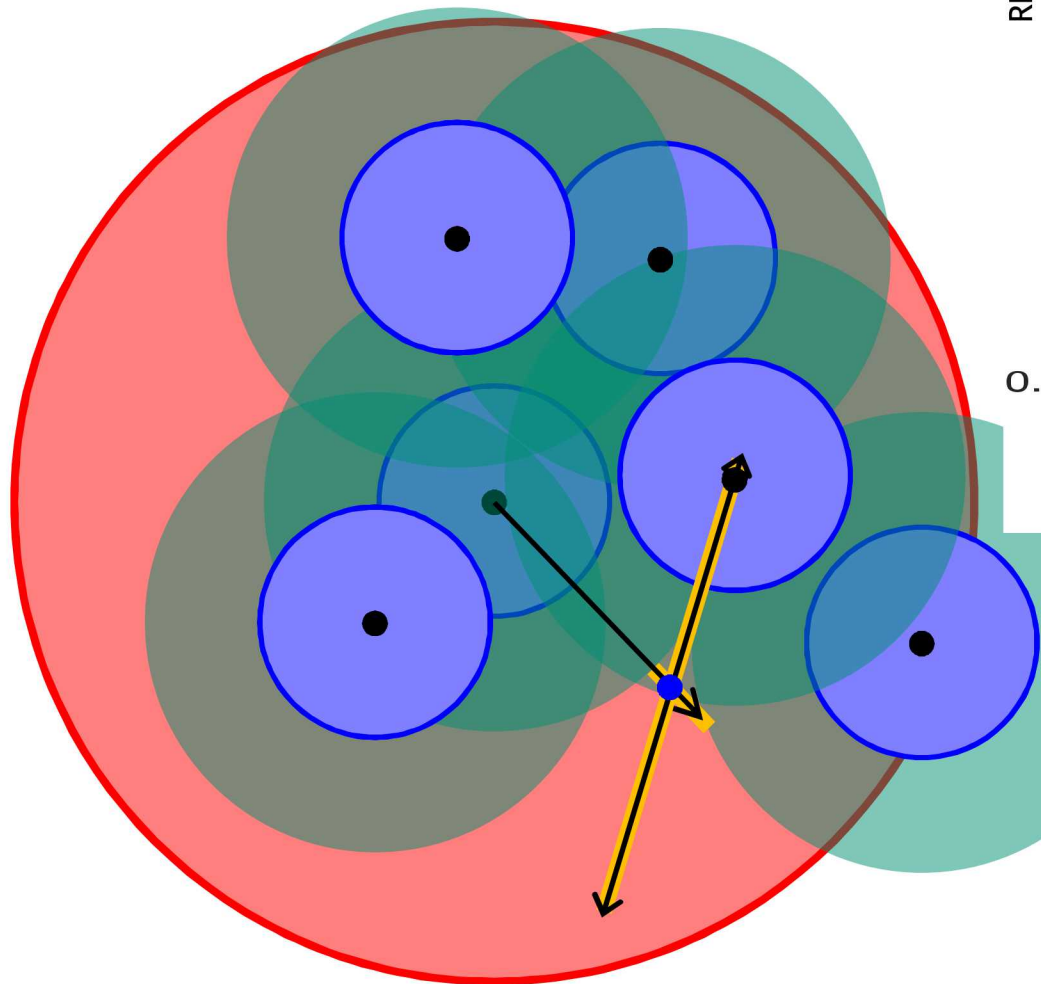


Eliminate spike

- † **Two-radii**: $r_{\text{free}} \neq r_{\text{cover}}$
 - Small blue r_{free} minimum sample separation
 - Large green r_{cover} maximum domain-to-sample
 - Unique coverage: accept only if covers white

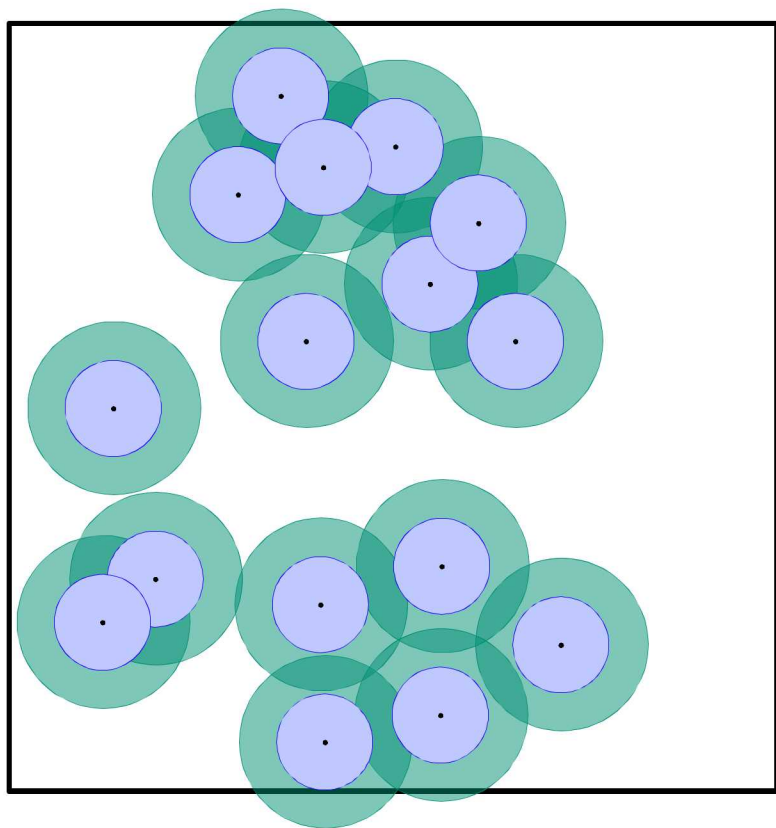


- Two-spokes** mimic Two-radii
 - 1st spoke, trim by large green
 - 2nd spoke, trim by small blue

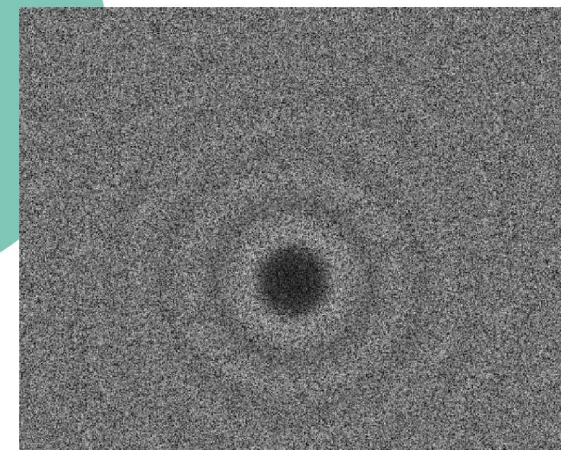
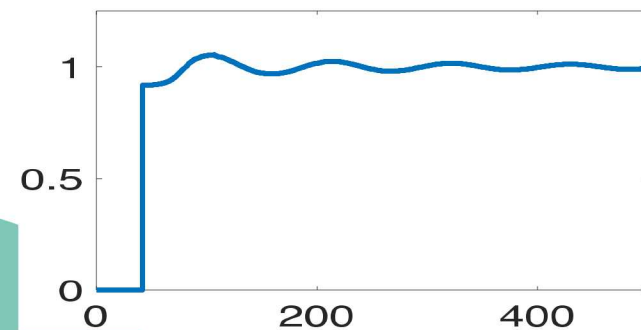
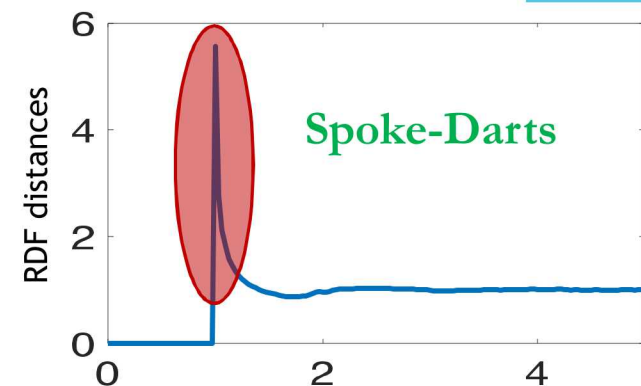
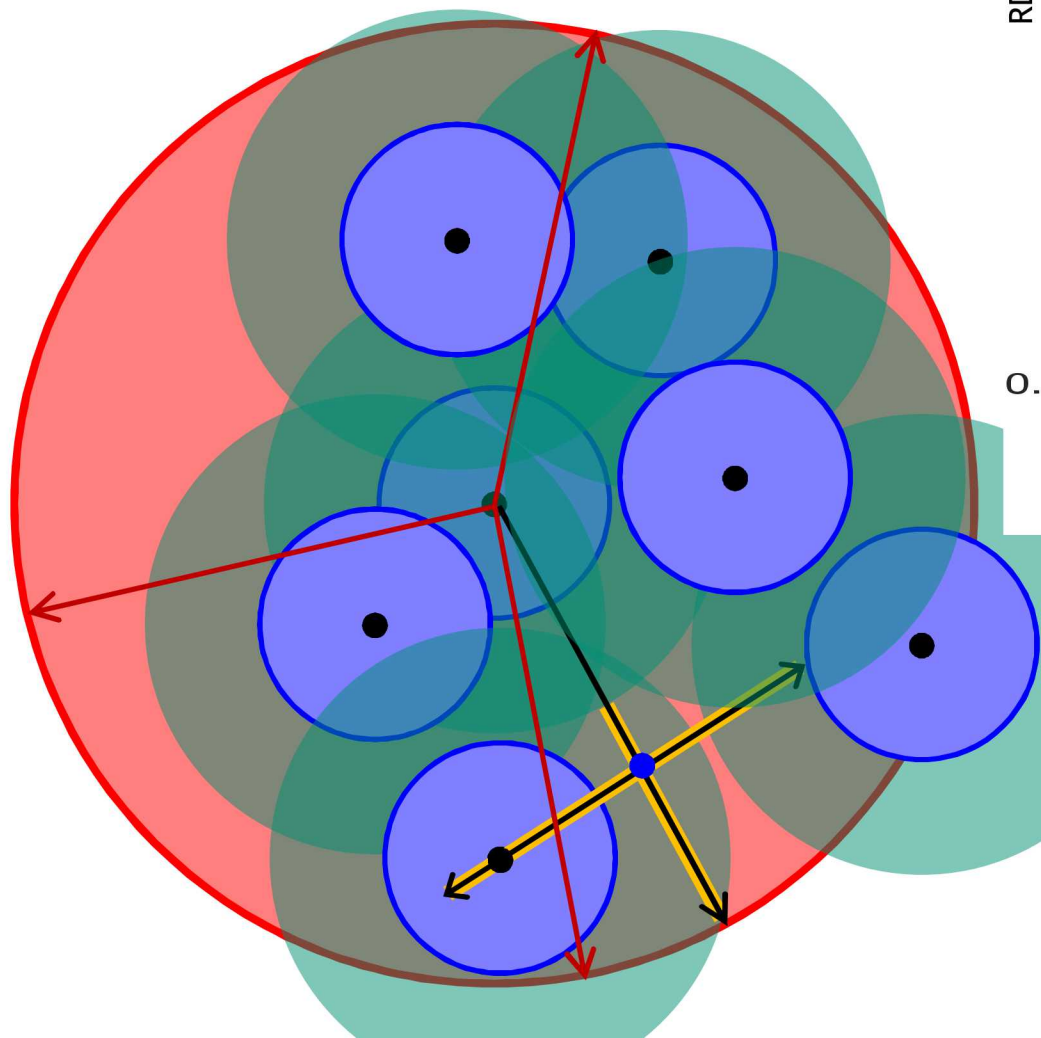


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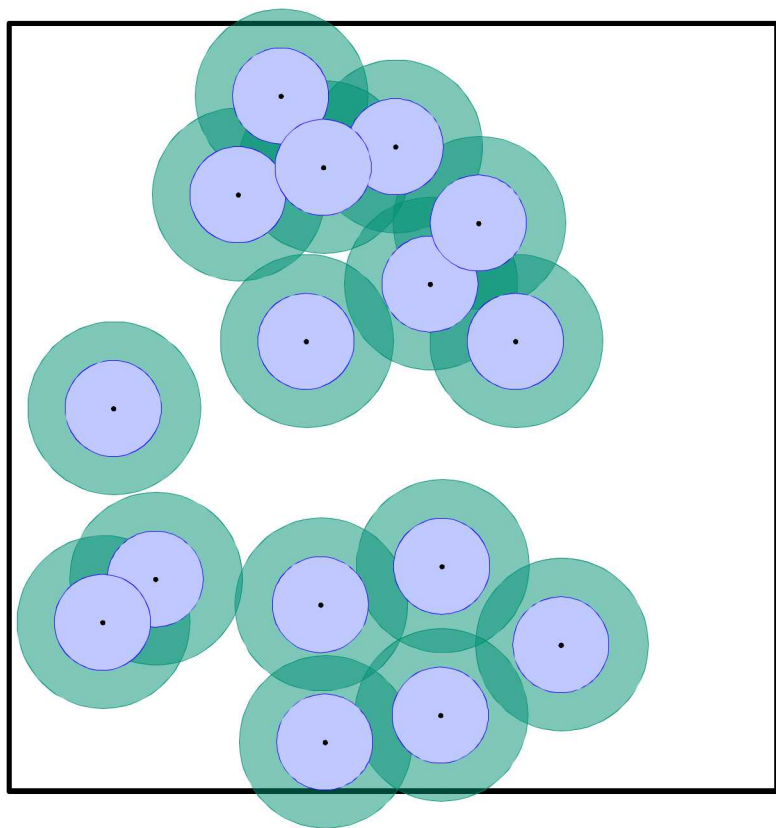


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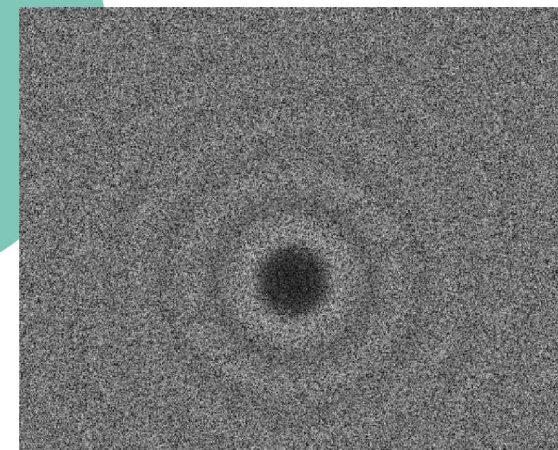
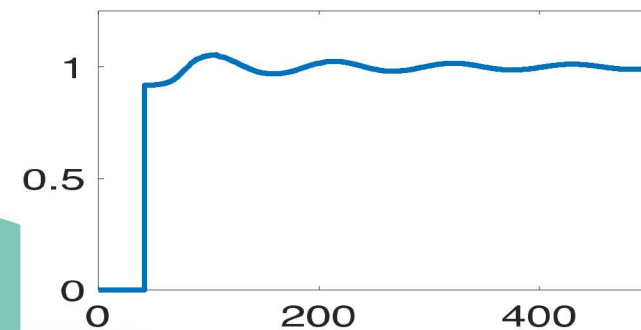
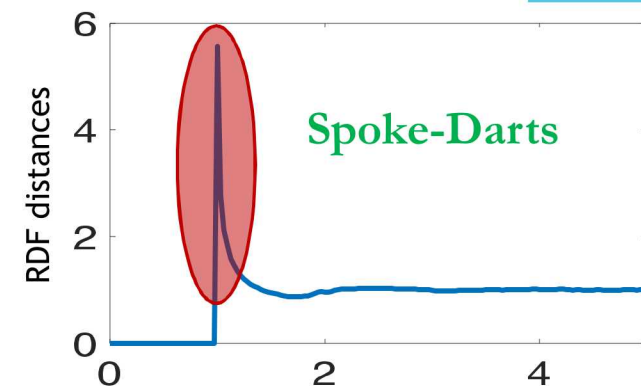
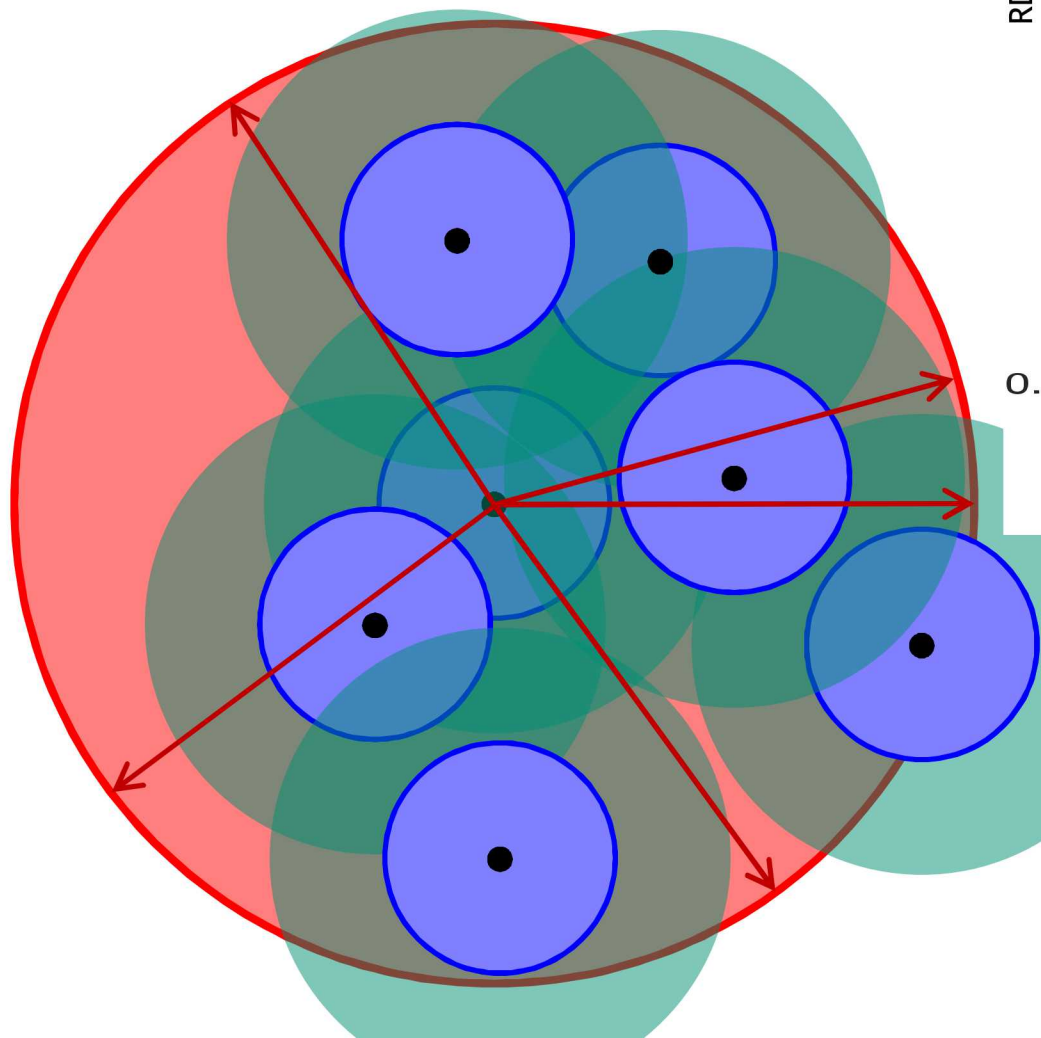
Eliminate spike

- † **Two-radii**: $r_{\text{free}} \neq r_{\text{cover}}$
 - Small blue r_{free} minimum sample separation
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 - Unique coverage: accept only if covers white



- Two-spokes** mimic Two-radii

- 1st spoke, trim by large green
- 2nd spoke, trim by small blue



Output Randomness – Blue noise

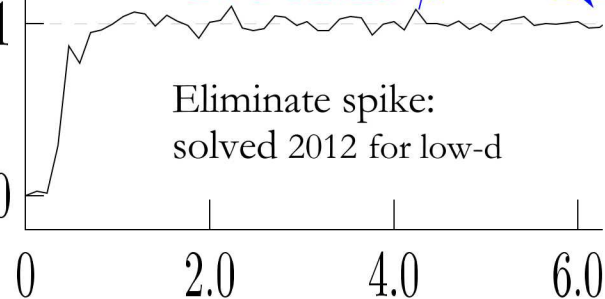
Flat spectrum
no spikes

d=2

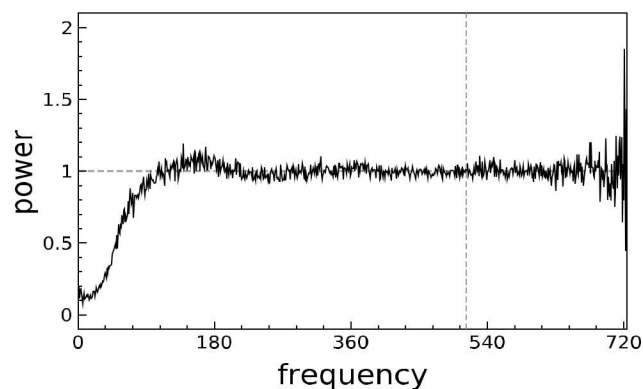
Pairwise distances
between samples

MPS (One-Radii) $\beta^* = 1$
Two-Radii $\beta^* = 2$

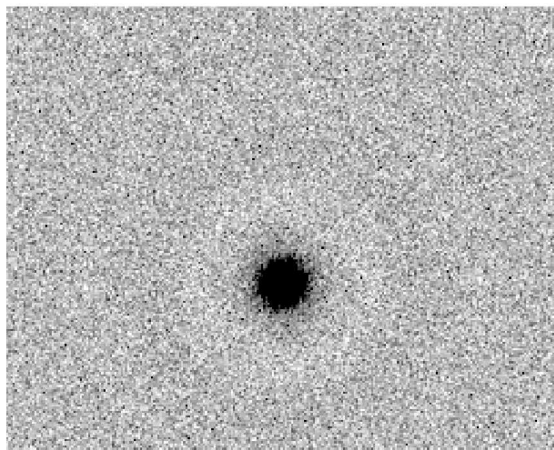
Eliminate spike:
solved 2012 for low-d



Fourier Transform, 1d
integral over angle by radius



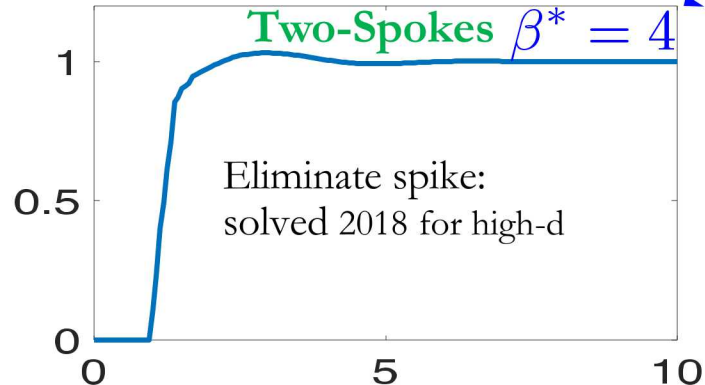
Fourier Transform



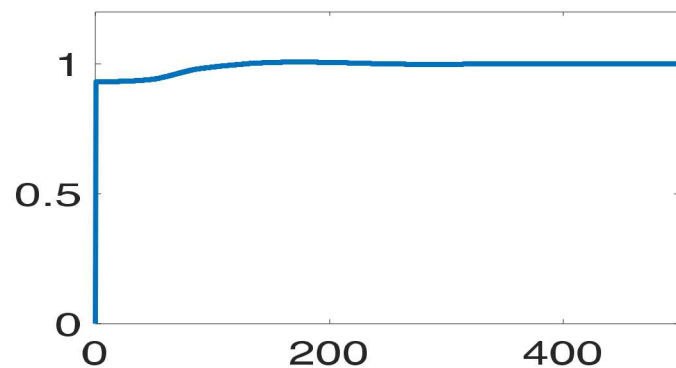
RDF distances

Two-Spokes $\beta^* = 4$

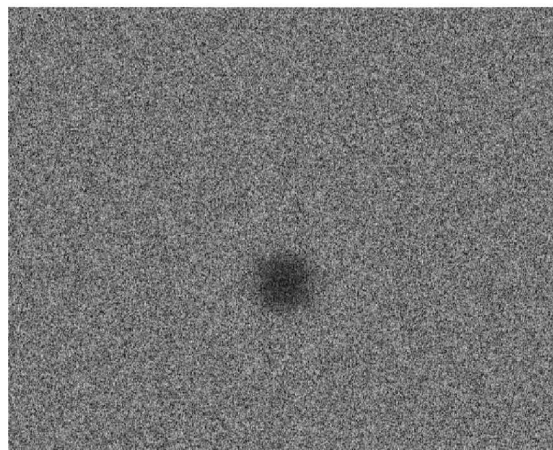
Eliminate spike:
solved 2018 for high-d



RP frequency

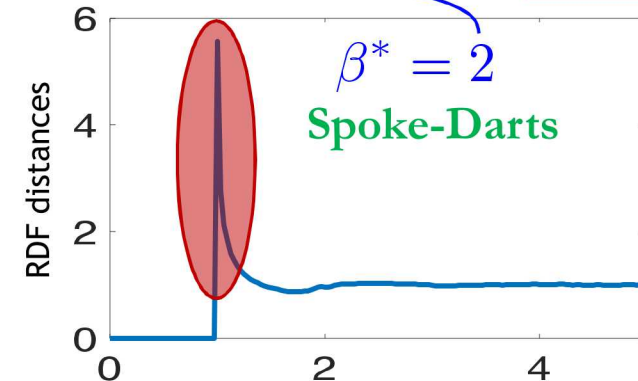


frequency

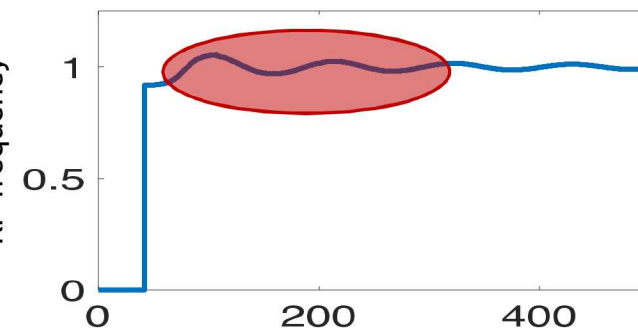


RDF distances

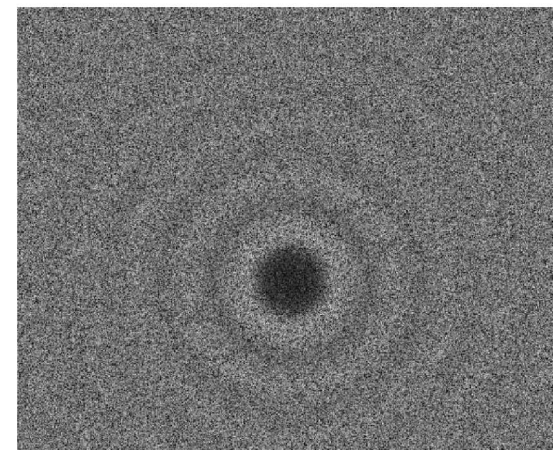
$\beta^* = 2$
Spoke-Darts



RP frequency

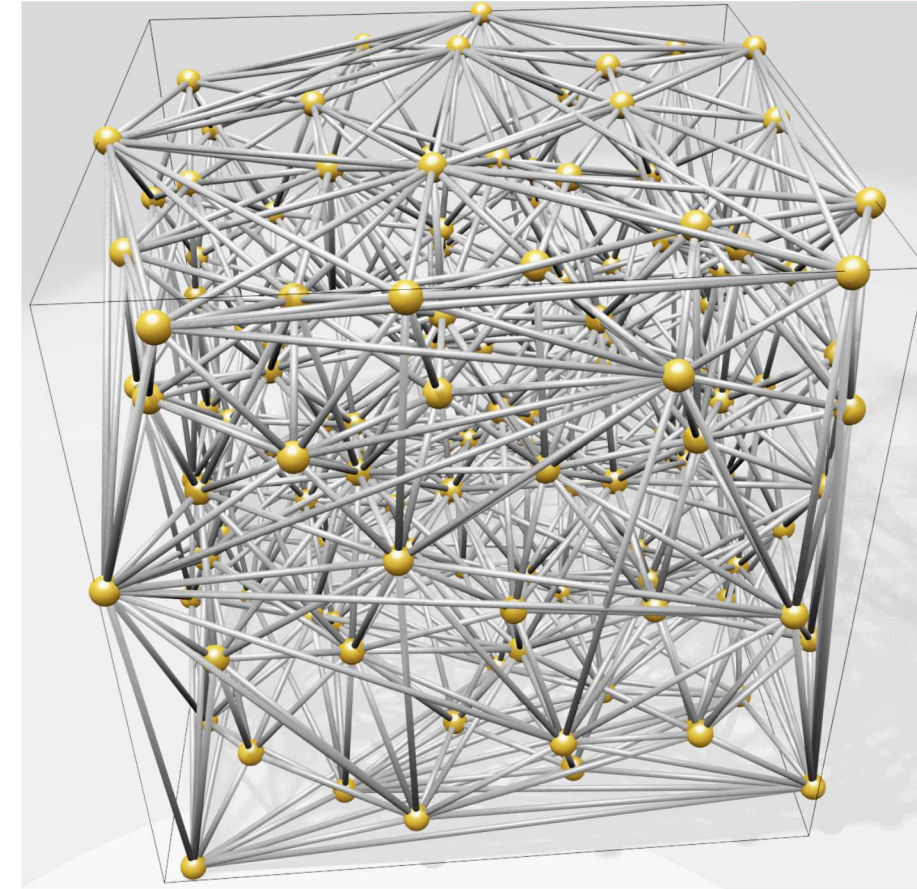
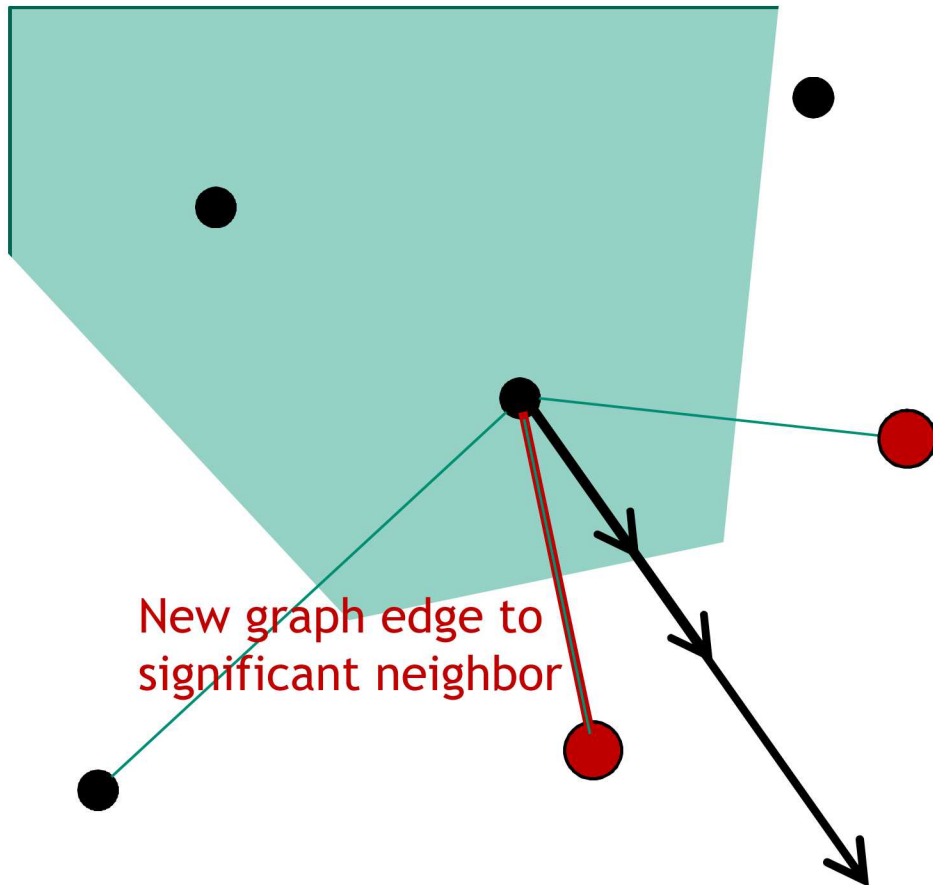


frequency



Application: Approximate Delaunay Graph

Trim line-spokes to find “significant” neighbors in Voronoi diagram



3d rendering of 8d graph

Application: Global Optimization

DIRECT = DIviding RECTangles

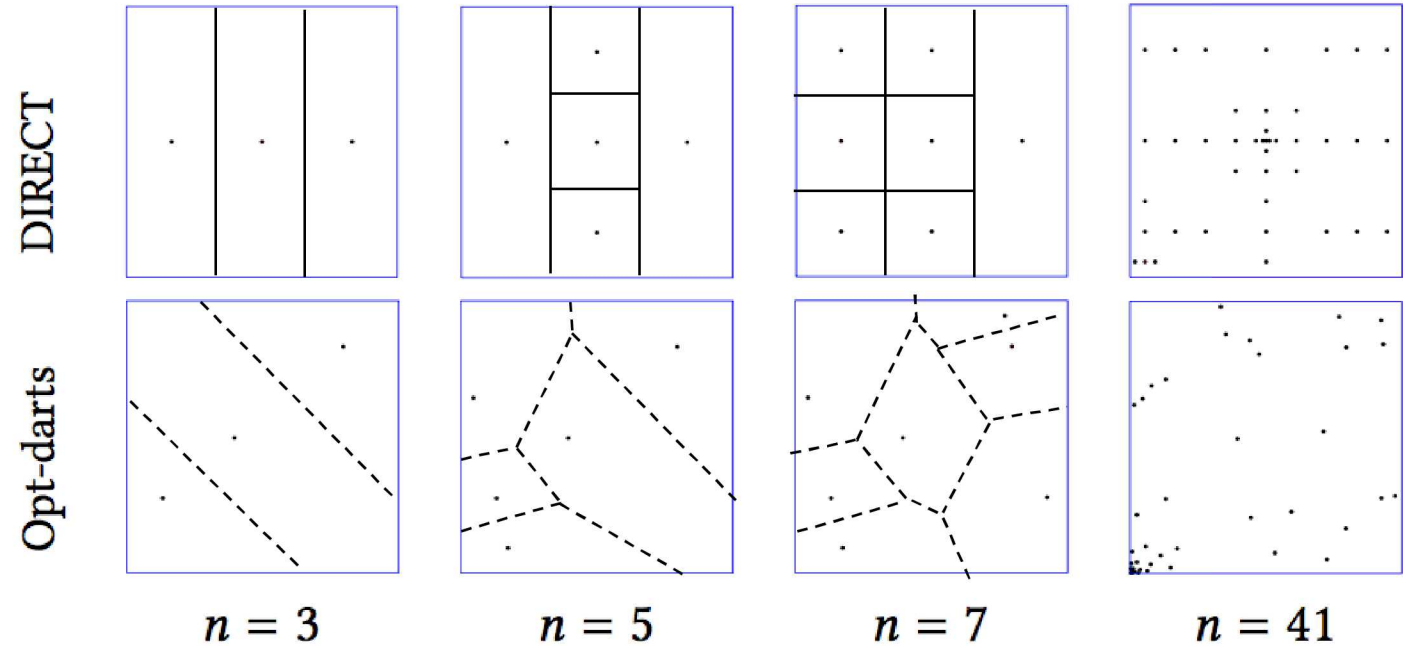
- Divide space by rectangles
- Refine large rectangles with small sample values

Opt-Darts

- Divide space by Voronoi cells (*implicit only*)
- Refine large cells with small sample values
 - Approx. Delaunay graph defines “large” cells
 - Spoke-darts selects refinement sample

Opt-Darts: 5-25× speedup over DIRECT

- Increasing speedup with d
 - Rectangle bad approximation of Voronoi cell
- More-random sample patterns



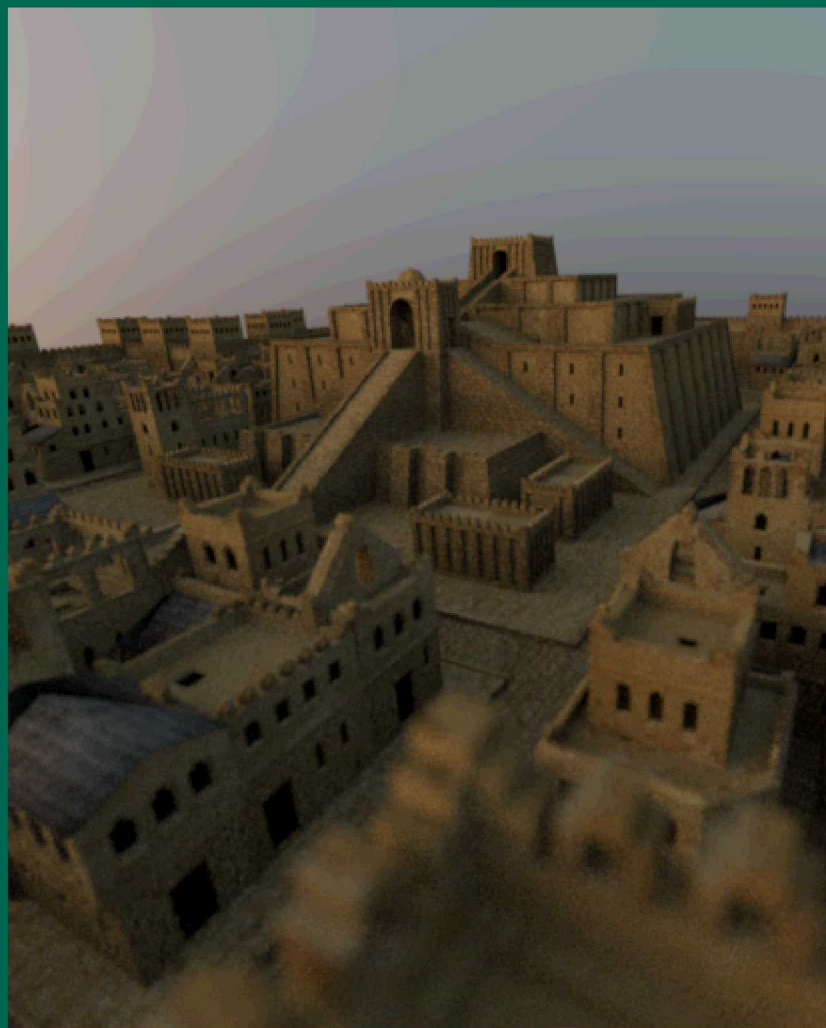
Application: Rendering

Mitsuba ray tracing

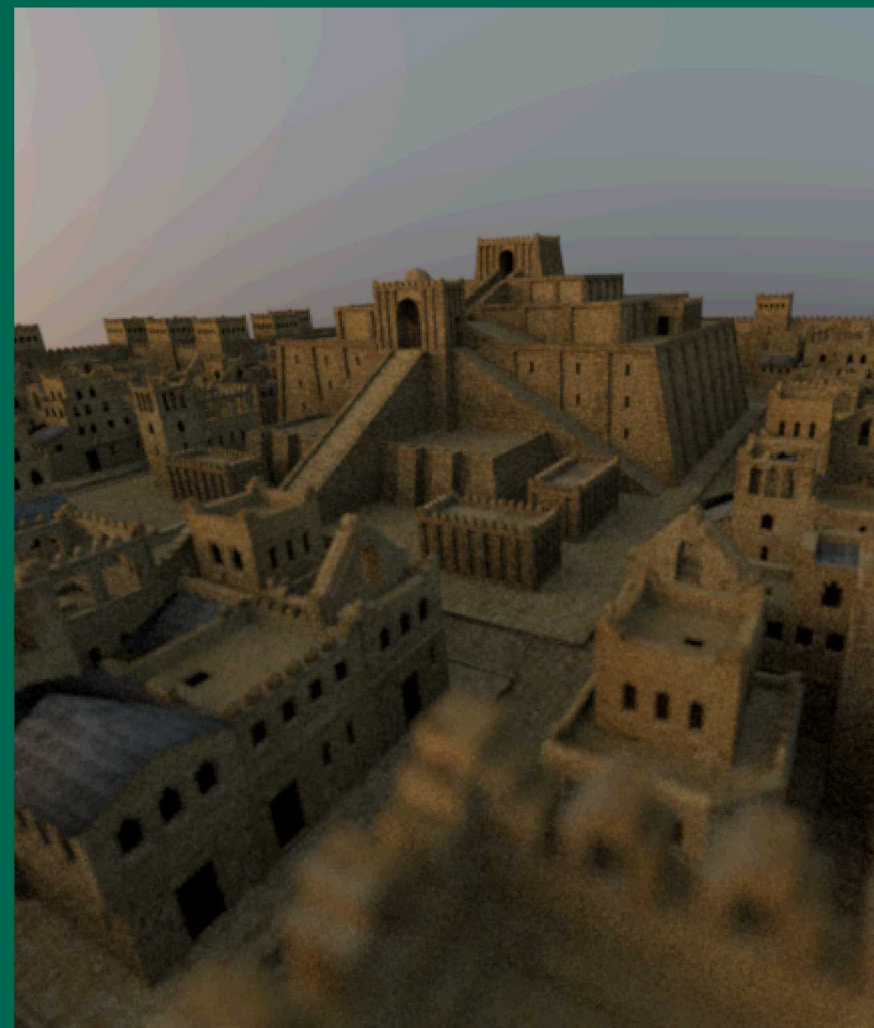
- $4D = 2 \text{ screen} \times 2 \text{ lens}$
- 16 samples per pixel



Stratified



Low discrepancy

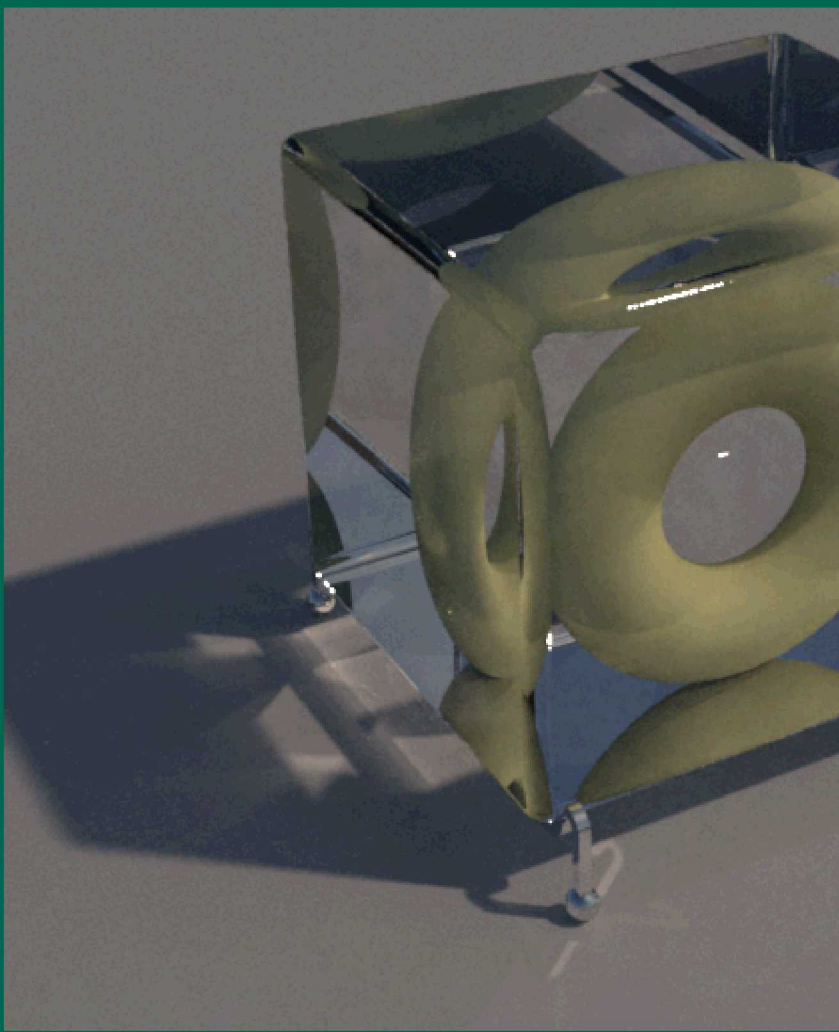


Spoke-darts
comparable to alternatives

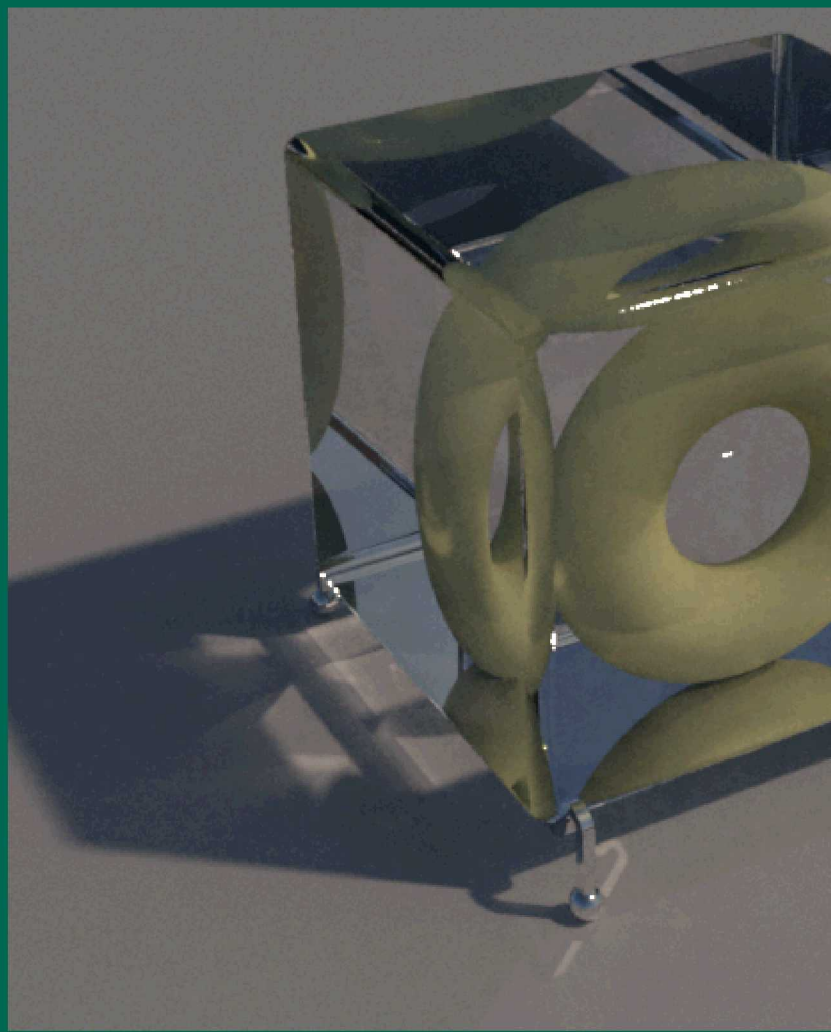
Application: Rendering

Mitsuba ray tracing

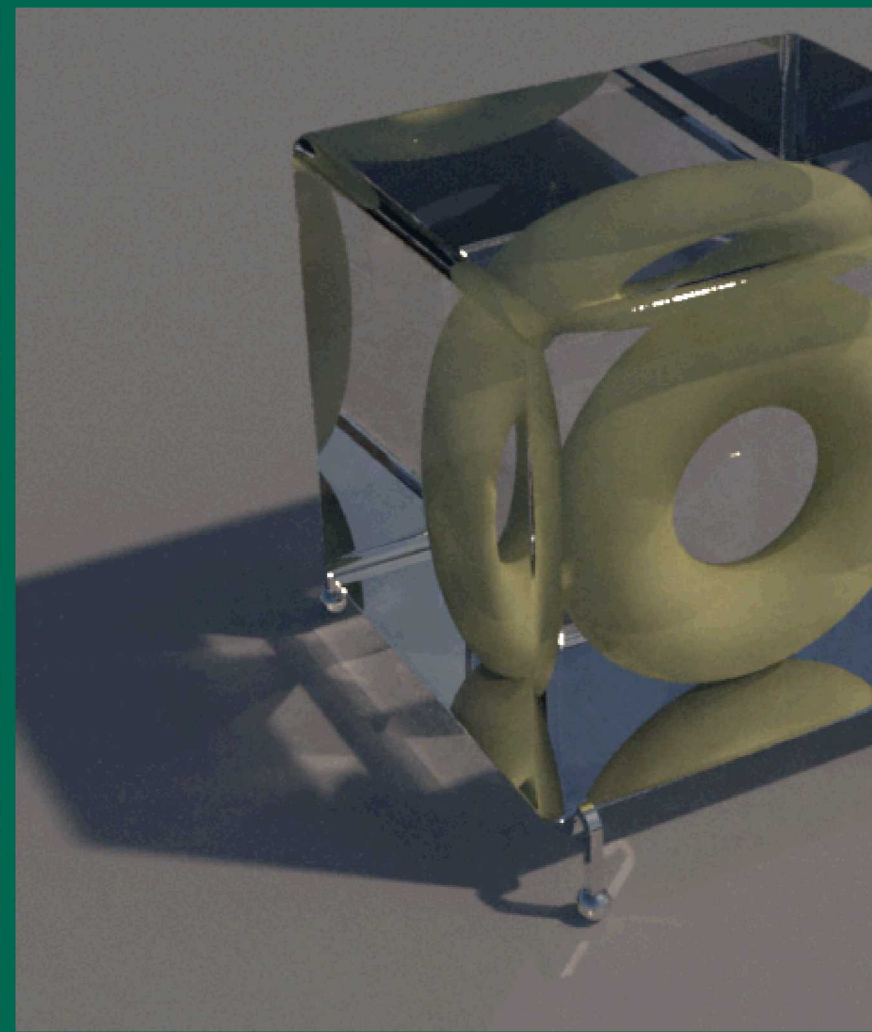
- $8D = 2 \text{ sky-emitter} \times 2 \text{ screen} \times 2 \times 2 \text{ bounce}$
- 256 samples per pixel



Stratified



Low discrepancy



Spoke-darts
comparable to alternatives

Application: Motion Planning

Path = robot: under table to up
book: table to shelf

23d = degree of freedom robot

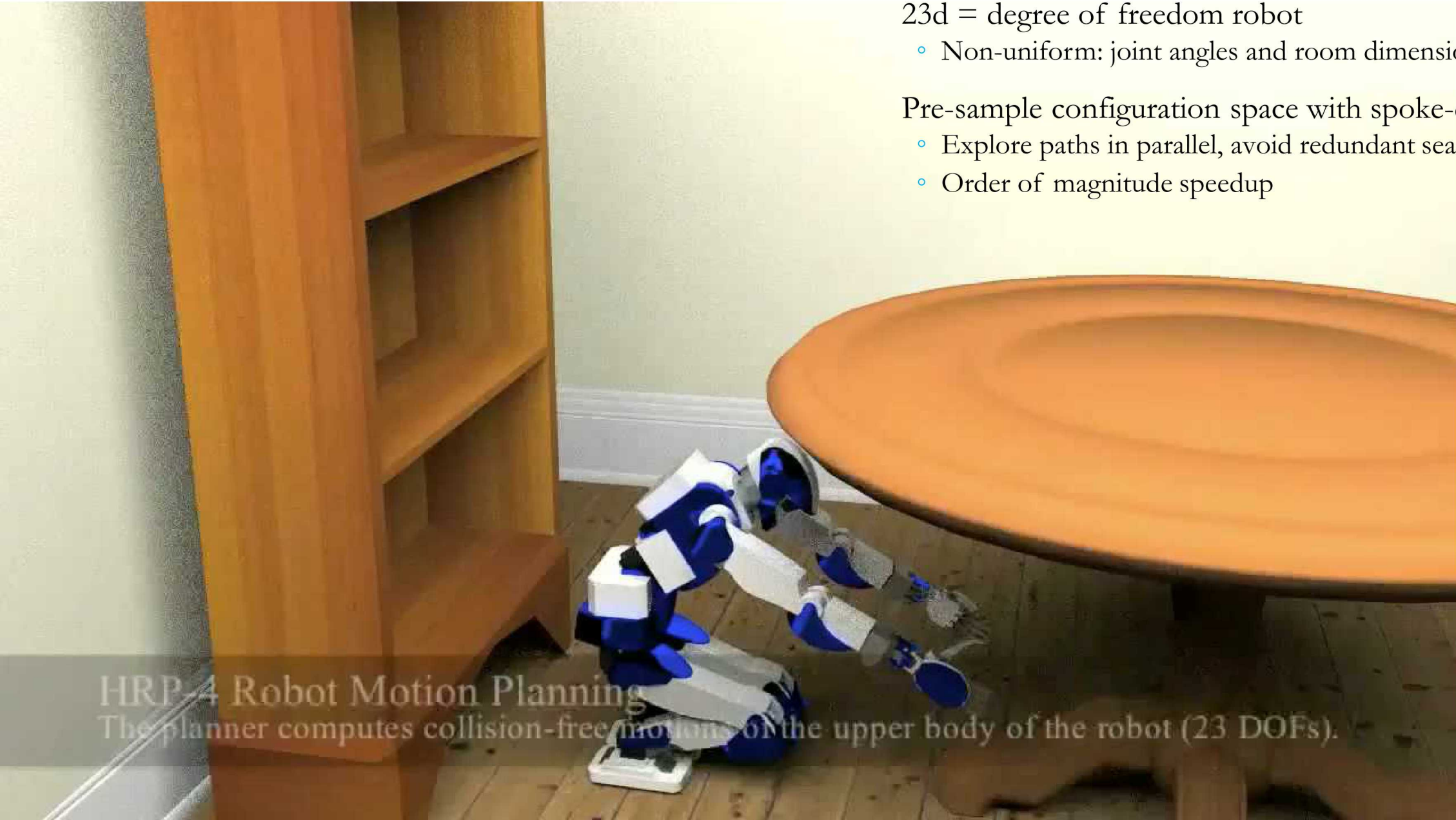
- Non-uniform: joint angles and room dimensions

Pre-sample configuration space with spoke-darts

- Explore paths in parallel, avoid redundant searches
- Order of magnitude speedup

HRP-4 Robot Motion Planning

The planner computes collision-free motions of the upper body of the robot (23 DOFs).





Free software

- SpokeDartsPublic on github
<https://github.com/samitch/SpokeDartsPublic>

Recommendations

Two-radii

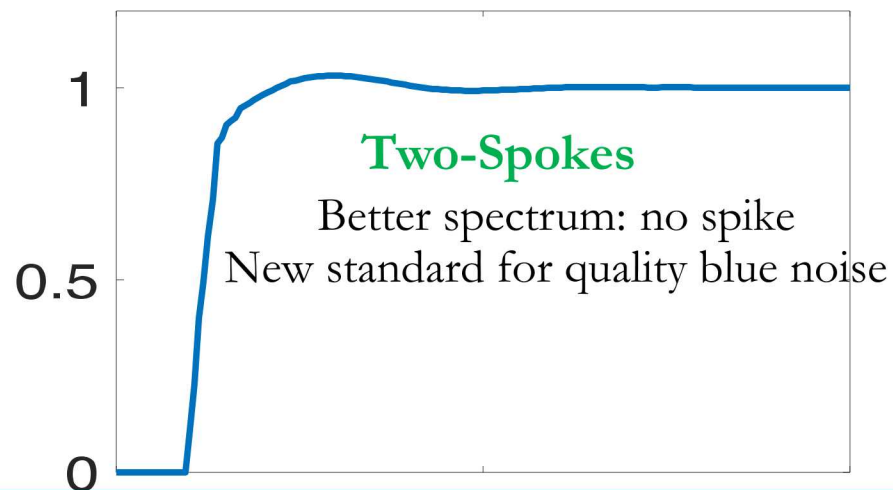
Quality blue-noise in $d < 5$

Spoke-Darts

Blue-noise $d \geq 5$

Linear scaling by dimension

Guaranteed saturation



Open problems

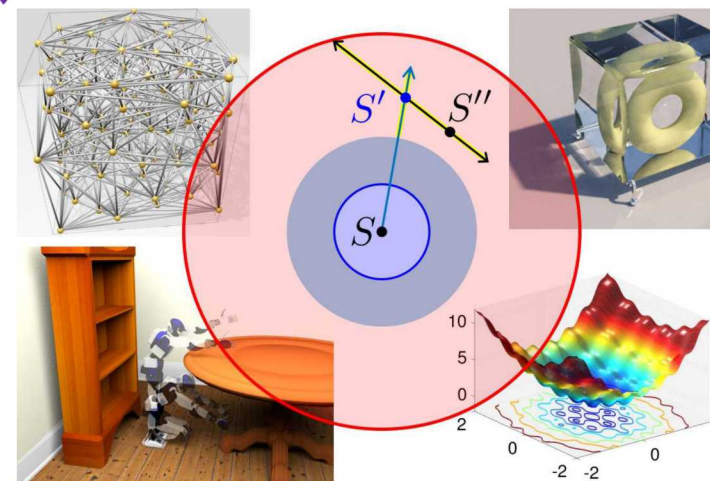
- Faster than $O(d n^2)$ time?
- Our experiments had $r_{\text{cover}} = 2 r_{\text{free}}$
 - Spectrum effects for other ratios?
- Prove non-trivial saturation-bound on Bridson 2007?
- Does saturation matter for high-d rendering, other “Graphics” applications ?

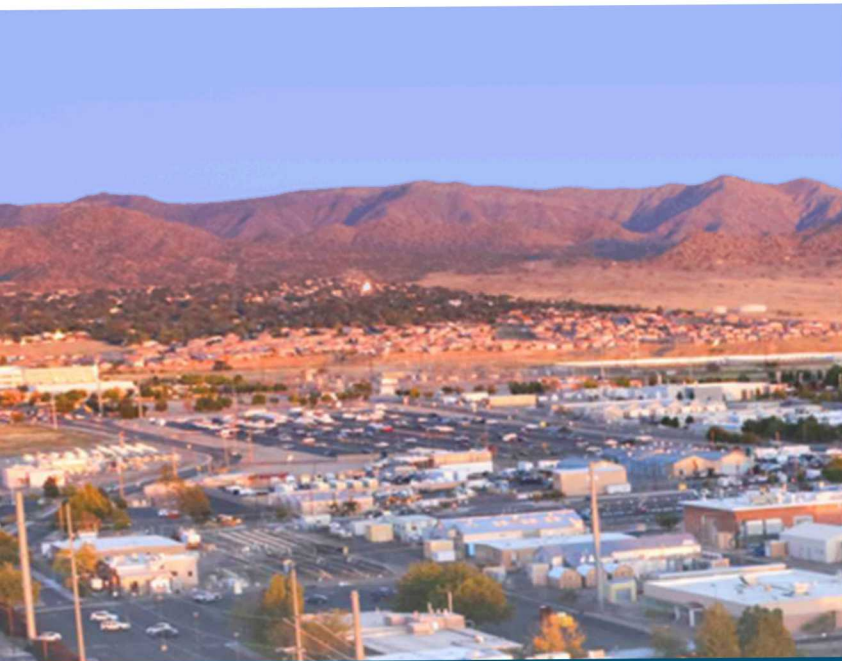
Geometry

Render

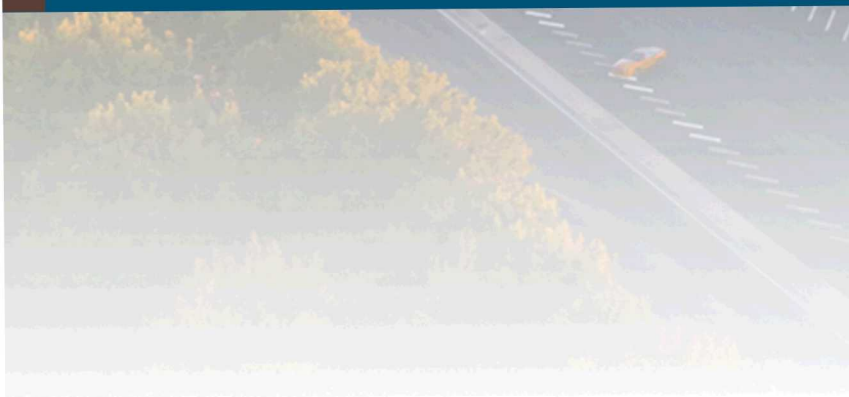
Motion Plan

Optimize

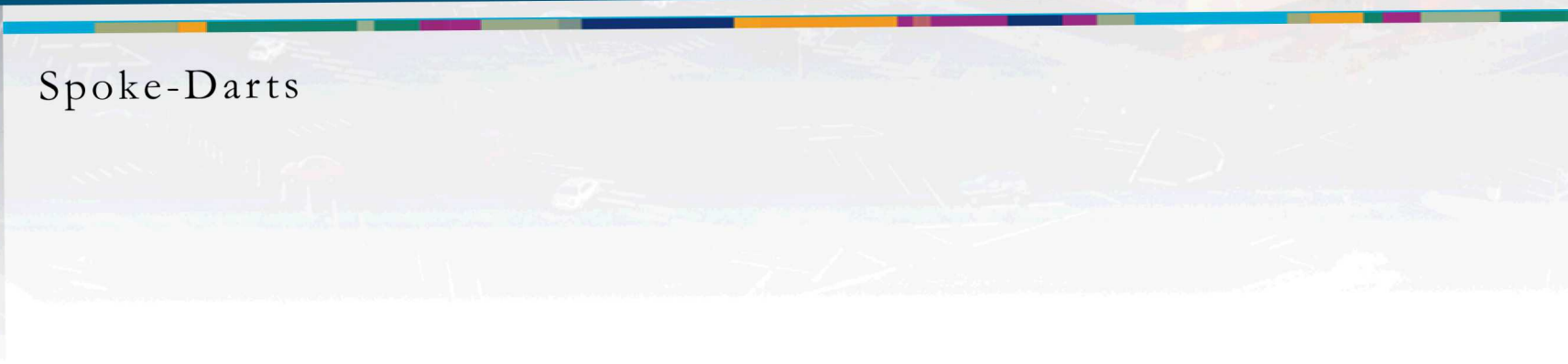




Backup slides



Spoke-Darts



Runtime = $O(dn^2)$, best one can hope for

d

- Linear scaling is perfect: primitives are $O(d)$

n^2

- Finding neighbors in high dimensions expensive
- Each of n samples, find neighbors
- Each of n may have n neighbors
 - Finding them quickly still won't prevent n^2

Spoke-Darts \approx Bridson 2007 due to simple primitives

- Is point in sphere
- Trim segment by sphere

Runtime(Two-Spokes) > Runtime(One-Spoke)

- mostly due to $2 \times$ radius of annulus, many more neighbor disks

31 Spectra by dimension

