

# Let the Physics Do the Work: Scattering Algorithms for High-Dimensional Geometry

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# What is the algorithm (what do we design)?

## What is the input?

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### Quantum circuits

algorithm: a series of unitary operators

input: a unitary operator that queries an oracle

### Adiabatic quantum computing

algorithm: an initial Hamiltonian and an interpolation scheme

input: a term in the final Hamiltonian

### Quantum walks, a.k.a. scattering algorithms

input: a Hamiltonian, e.g. the adjacency matrix of a graph

algorithm: Schrödinger's equation

# Continuous time: Analog Analogue of Grover [Farhi & Gutmann 98]

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An unknown marked state  $v$ , and a known initial state  $u$

A Hamiltonian

$$H = |u\rangle\langle u| + |v\rangle\langle v|$$

The algorithm:

$$-i\hbar \frac{\partial}{\partial t} \psi = H\psi .$$

Start in  $u$ . At time

$$t = \frac{\pi}{2\langle u, v \rangle}$$

the state is  $v$ !

# Quantum walks

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Input: a Hamiltonian, e.g., the adjacency matrix of a graph

Algorithm: Schrödinger's equation

Mixing on the cycle [Ambainis et al., Aharonov et al.]

Mixing and hitting on the hypercube [Moore, Russell; Kempe]

Exponential speedup possible [Childs et al.]

Element distinctness [Ambainis]

Search in  $d$  dimensions [Ambainis, Kempe, Rivosh; Childs, Goldstone]

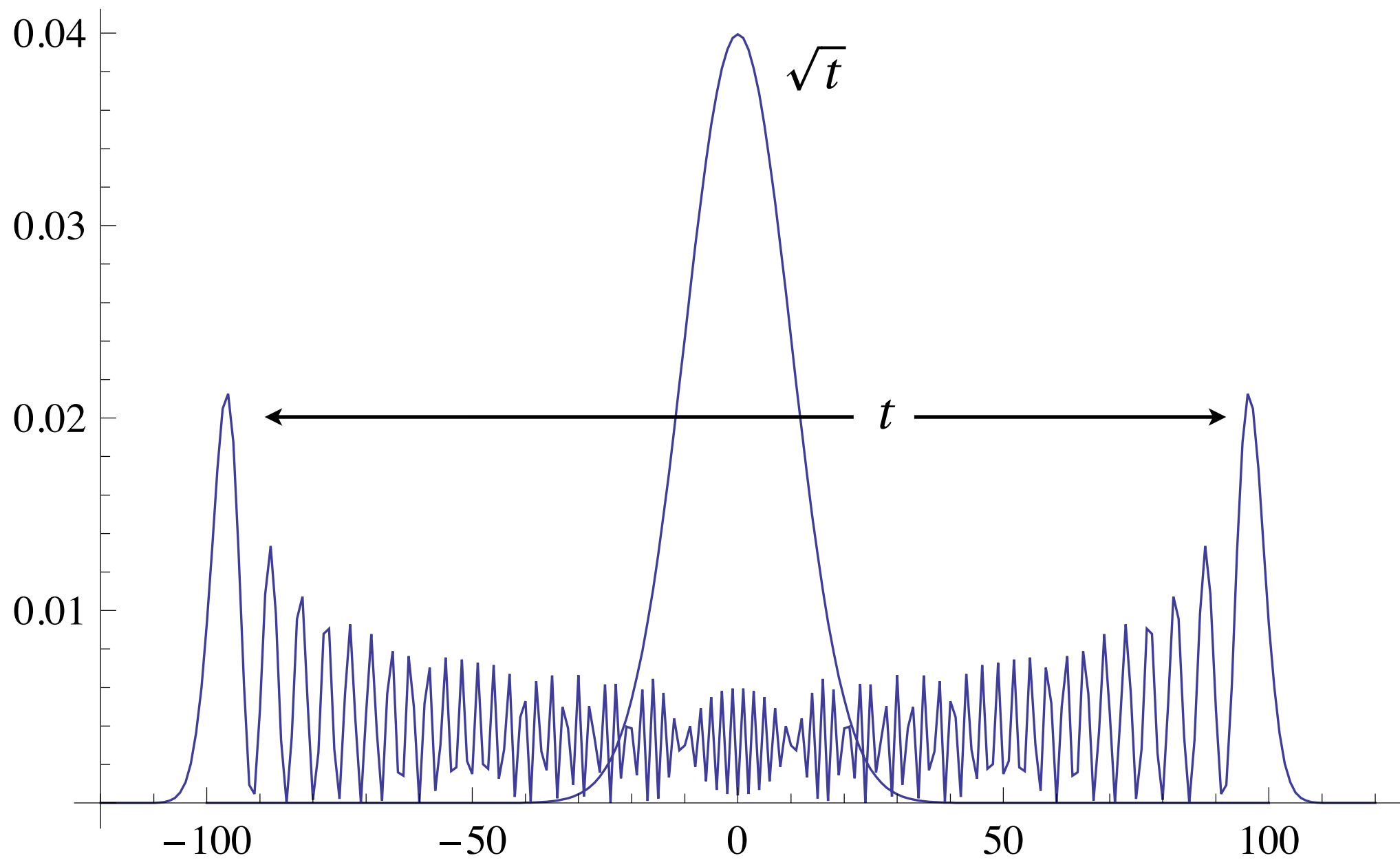
Hidden nonlinear structures [Childs, Schulman, Vazirani]

NAND trees [Farhi, Goldstone, Gutmann]

Boolean formulas [Reichardt, Spalek; Ambainis et al.]

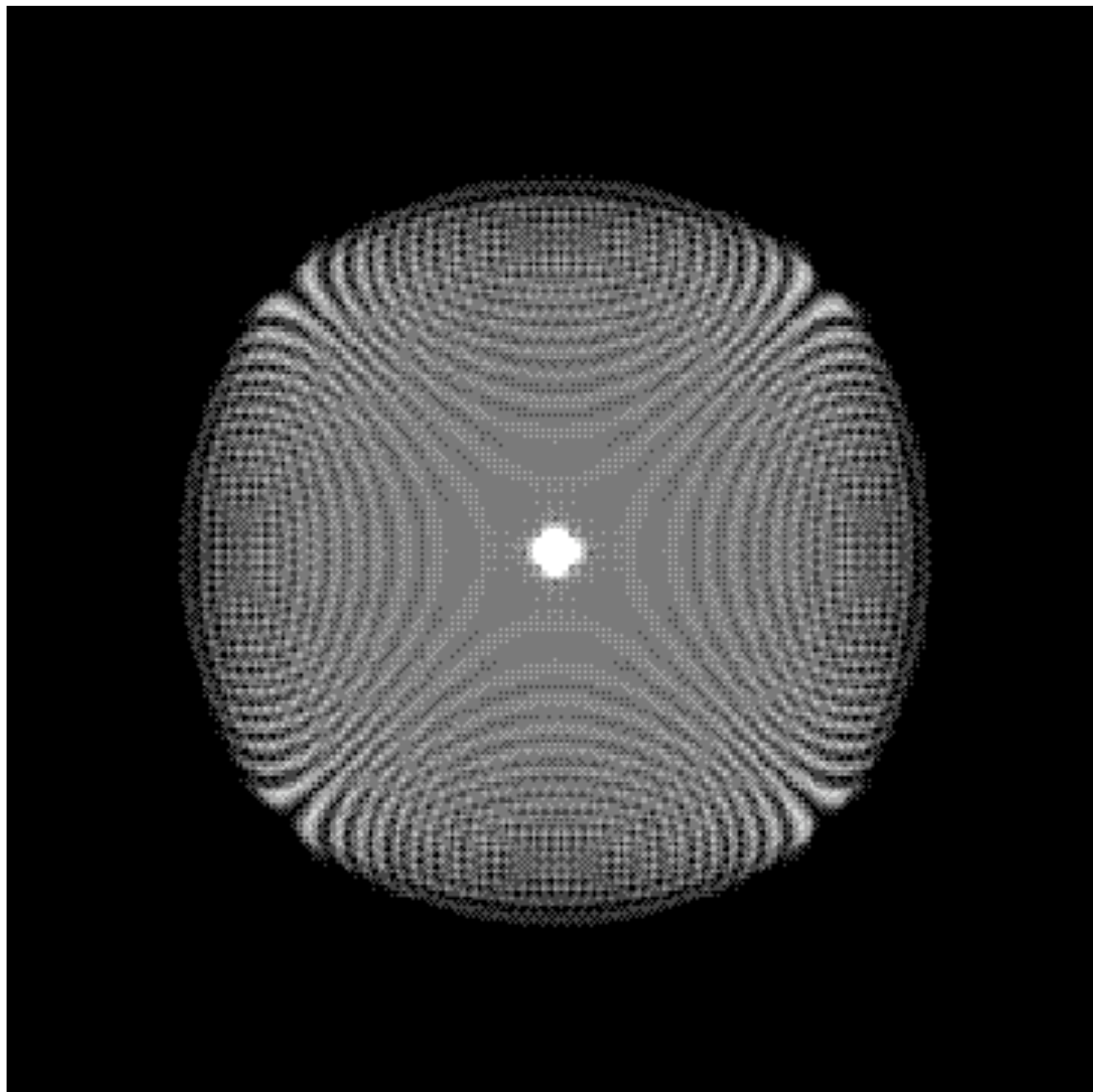
# Quantum walks

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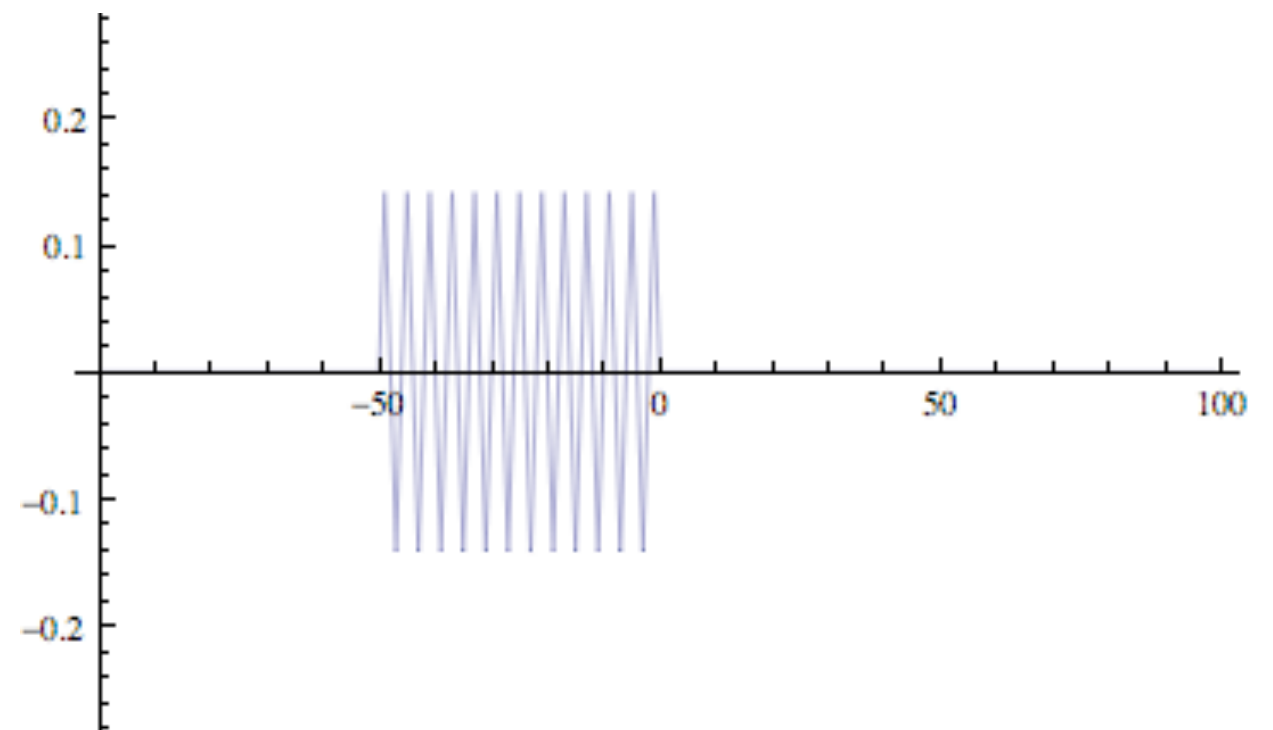
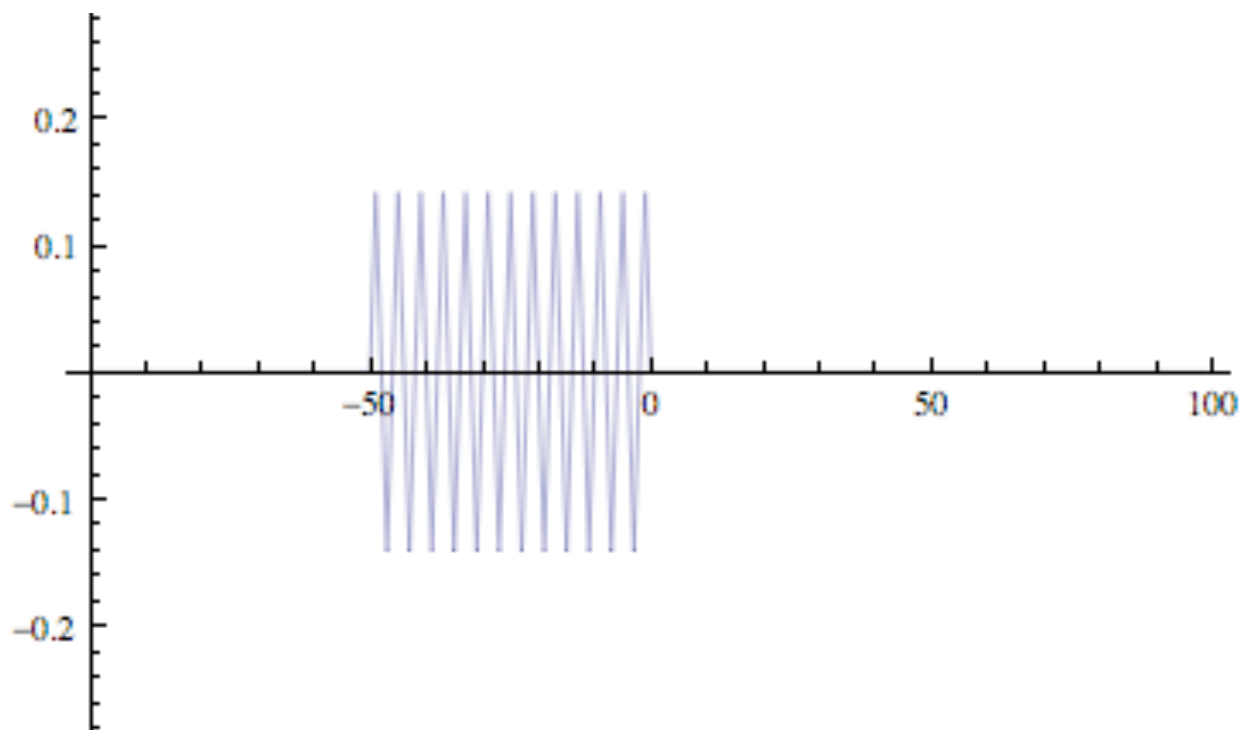
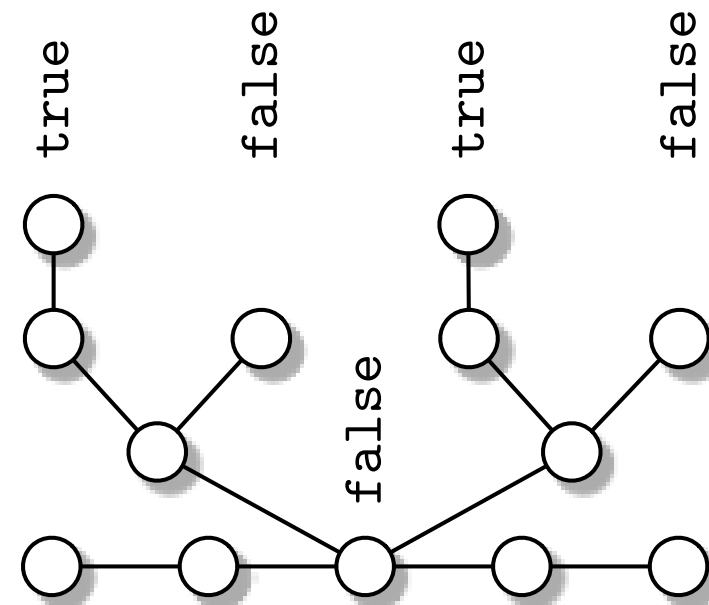
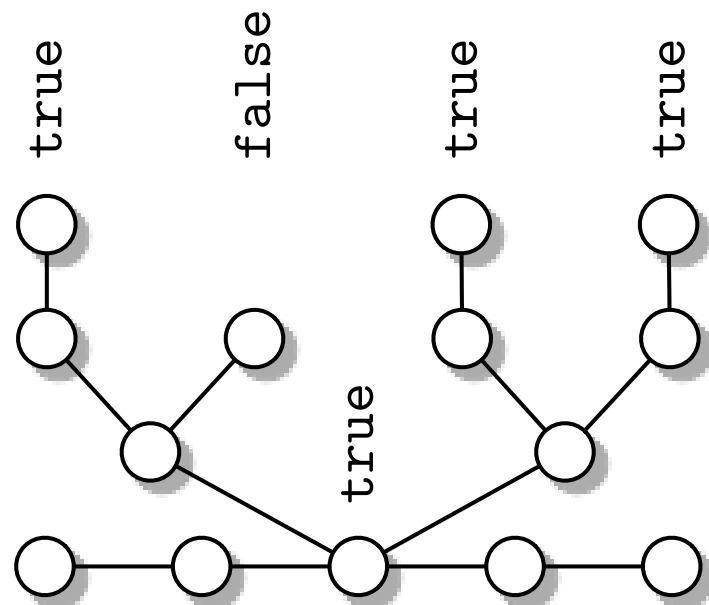


# Quantum walks

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# NAND trees in motion



# First-semester quantum algorithms

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Hamiltonian for a free particle in  $\mathbb{R}^n$  with zero potential:

$$H = \frac{p^2}{2m} = -\hbar^2 \frac{\nabla^2}{2m}.$$

Equivalent to quantum walk on the  $n$ -dimensional lattice in the low-energy limit

What can we learn about the initial state, simply by running Schrödinger's equation for a certain amount of time and measuring the position?



# Spherical shells

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Suppose the initial state is concentrated on a spherical shell of unknown center and/or unknown radius

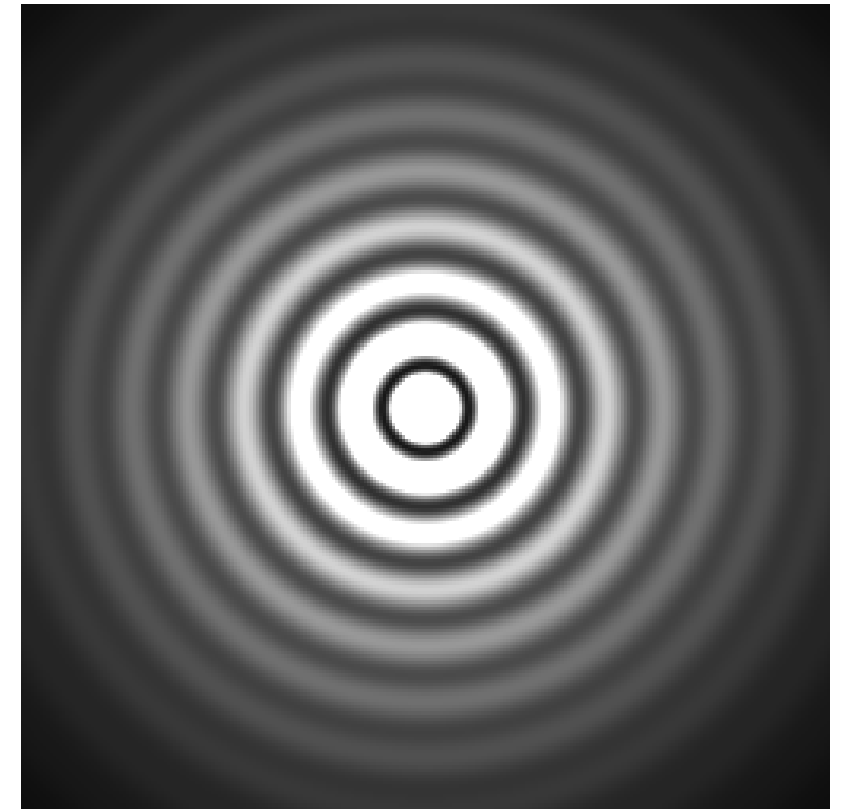
Application: finding the center of symmetry of a spherically symmetric function in  $R^n$

Let the initial thickness of the shell be  $w_0 \sim 1/\tau$

Evolve for time  $t \sim w_0^2 \tau$ , so the width of the state is roughly the radius of the sphere

As in geometric diffraction [Fresnel, Poisson, Arago] we get a bright spot at the center

Independent of the radius (up to a constant)



# How bright? A singularity at the center

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Density  $r$  away from the center: if  $r \gg nw_0$  the probability density scales as

$$|\psi|^2 \sim r^{-(n-1)}$$

so the probability density of the distance  $r$  is independent of  $n$ :

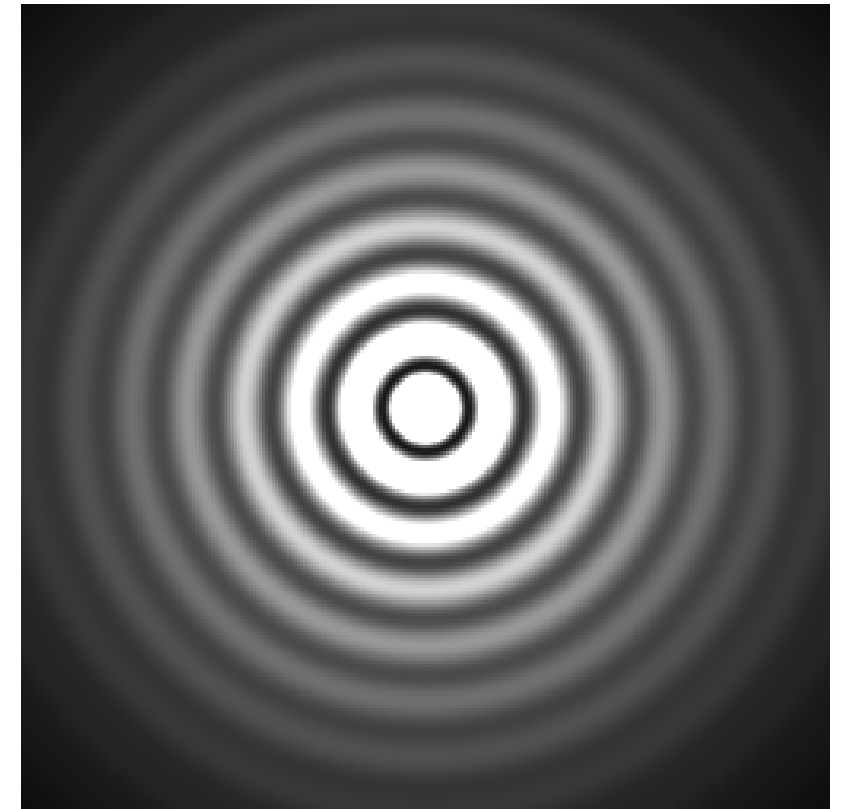
$$\rho(r) \sim 1$$

the total probability we observe a point at  $r < \varepsilon$  is

$$\Pr[r < \varepsilon] \sim \varepsilon$$

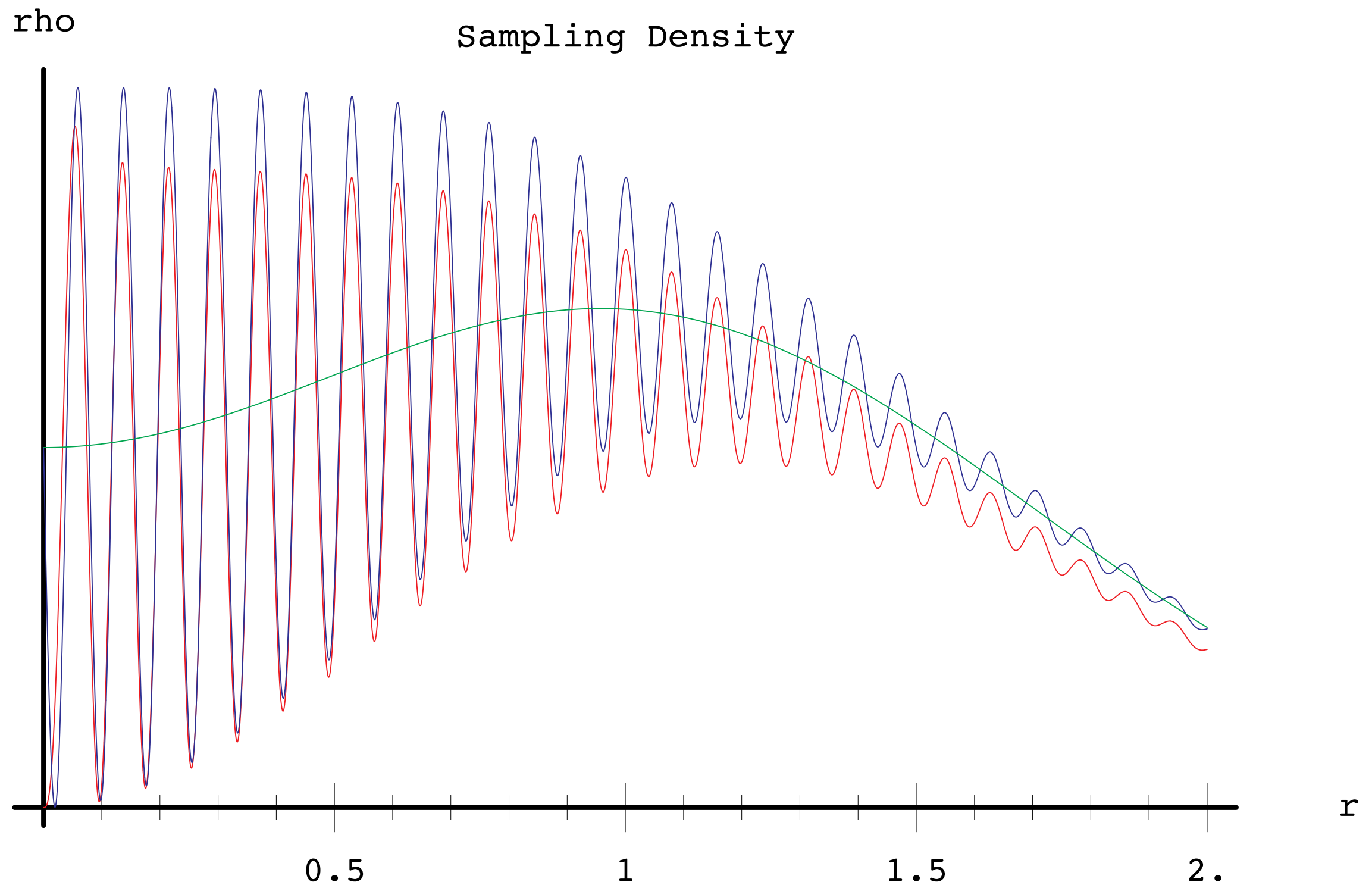
if  $|\psi|^2$  were smooth, this would be exponentially small

$$\Pr[r < \varepsilon] \sim \varepsilon^n$$



# Moiré and Bessel

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# Combining multiple samples

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Each sample has  $r < \varepsilon$  with probability

$$\Pr[r < \varepsilon] \sim \varepsilon$$

Toy model: each point is uniformly random on a sphere of radius  $r$ , where  $r$  is uniformly random in  $[0,1]$

How can we use  $s$  independent samples to obtain an estimate of the center with a very small  $\varepsilon$ ? And how many samples does this take?

The mean (or the median) gives

$$s \sim \varepsilon^{-2} \log n$$

which isn't any better than taking  $s$  samples from the original shell!

# Maximum likelihood

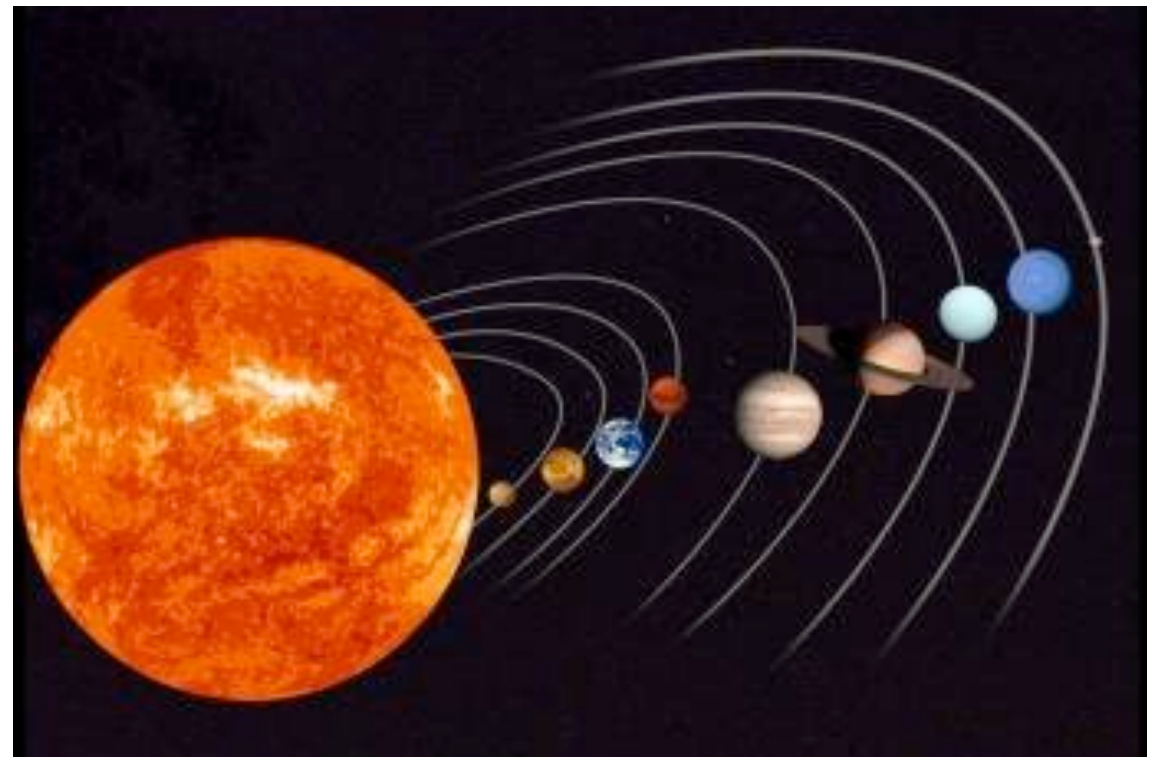
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Our estimate will be one of the samples

With  $s$  samples, the closest one probably is at distance

$$\varepsilon \sim 1/s$$

but how do we know which one is the closest?



# Maximum likelihood

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Since  $|\psi|^2 \sim r^{-(n-1)}$ , if  $x_i$  were the center, the probability that we see the other samples is proportional to

$$L = \prod_{j \neq i} |x_i - x_j|^{-(n-1)}$$

We renormalize away the “self-likelihood” of  $x_i$

Maximizing  $L$  is equivalent to minimizing the product of the distances

$$\prod_{j \neq i} |x_i - x_j|$$

Theorem: with probability bounded above zero, the  $x_i$  minimizing this product is the closest one

Gives error  $\varepsilon$  with just  $s \sim 1/\varepsilon$  samples

# Iterating to estimate the center of a spherically symmetric function

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In one round of  $s$  samples, we get an estimate with error  $\varepsilon \sim 1/s$

Create a uniform superposition in a ball around that estimate, sample in that ball to get a new estimate

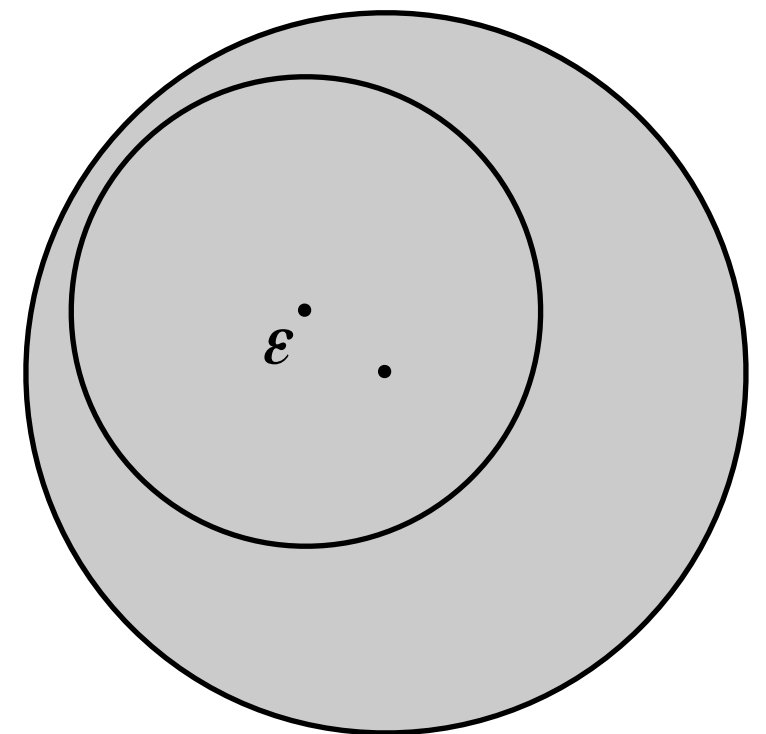
But this ball has to have radius  $n^{1/2}\varepsilon$  so the sampled shell has a large solid angle

Optimum scheme uses  $en^{1/2}$  samples in each round, so that the ball's radius decreases by a factor of  $e$  at each step

Total number of samples over all  $\log \varepsilon^{-1}$  rounds is then

$$s \sim n^{1/2} \log \varepsilon^{-1}$$

which is better than  $s \sim 1/\varepsilon$  if  $\varepsilon \ll n^{-1/2}$



# Yi-Kai Liu's algorithm

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Apply the *curvelet transform* to the sphere

Gives an approximate vector normal to a random point on the surface

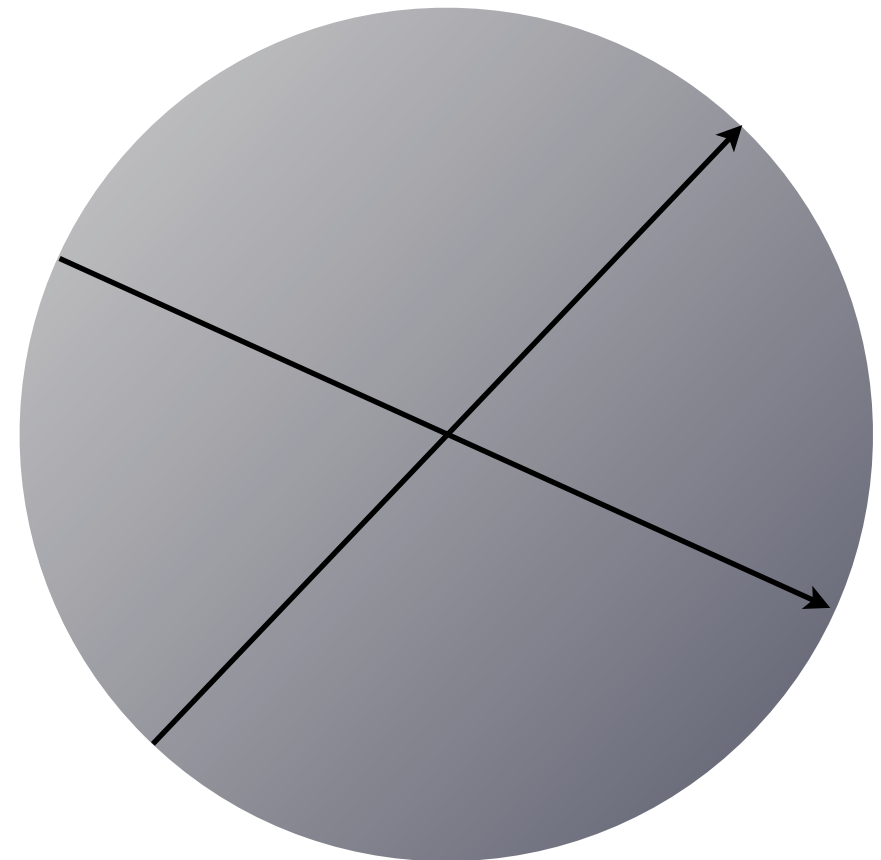
One measurement: choose a random point along that vector

Two measurements: find intersection between two such vectors

Estimates the center within error

$$\varepsilon \sim (n w_0)^{1/2}$$

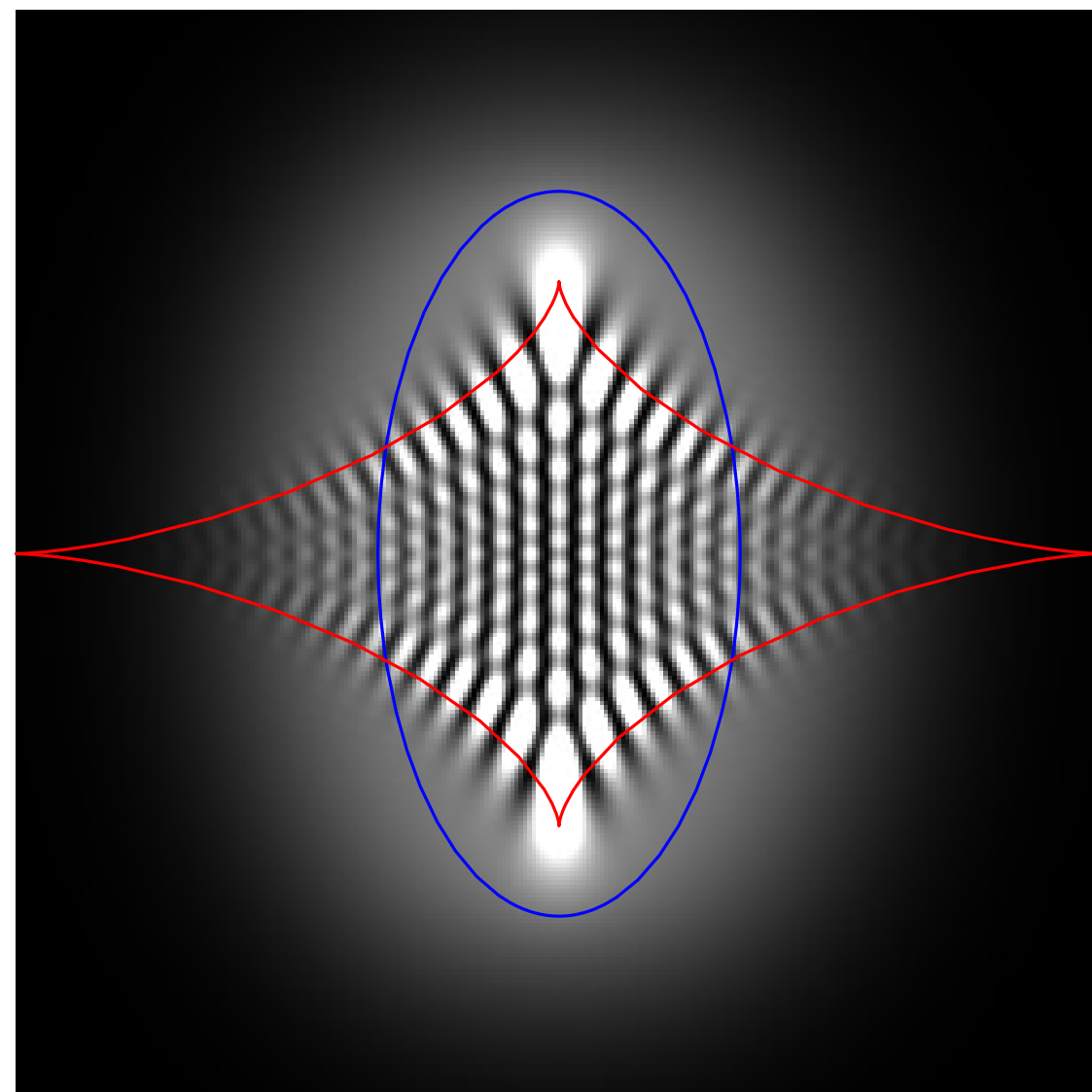
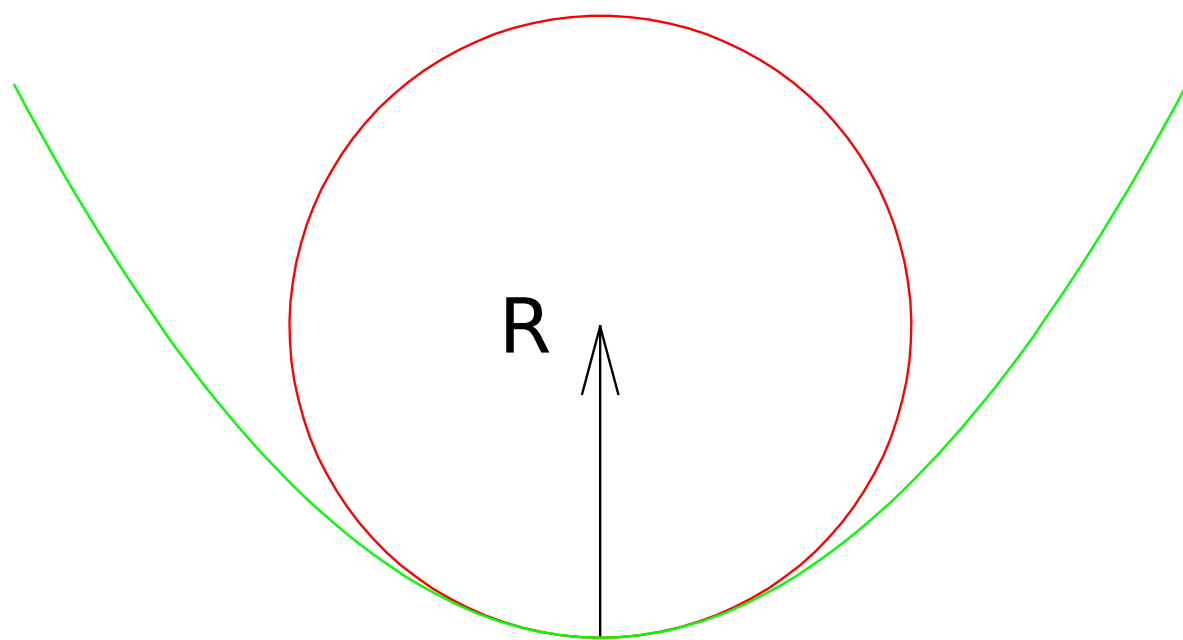
with just two queries





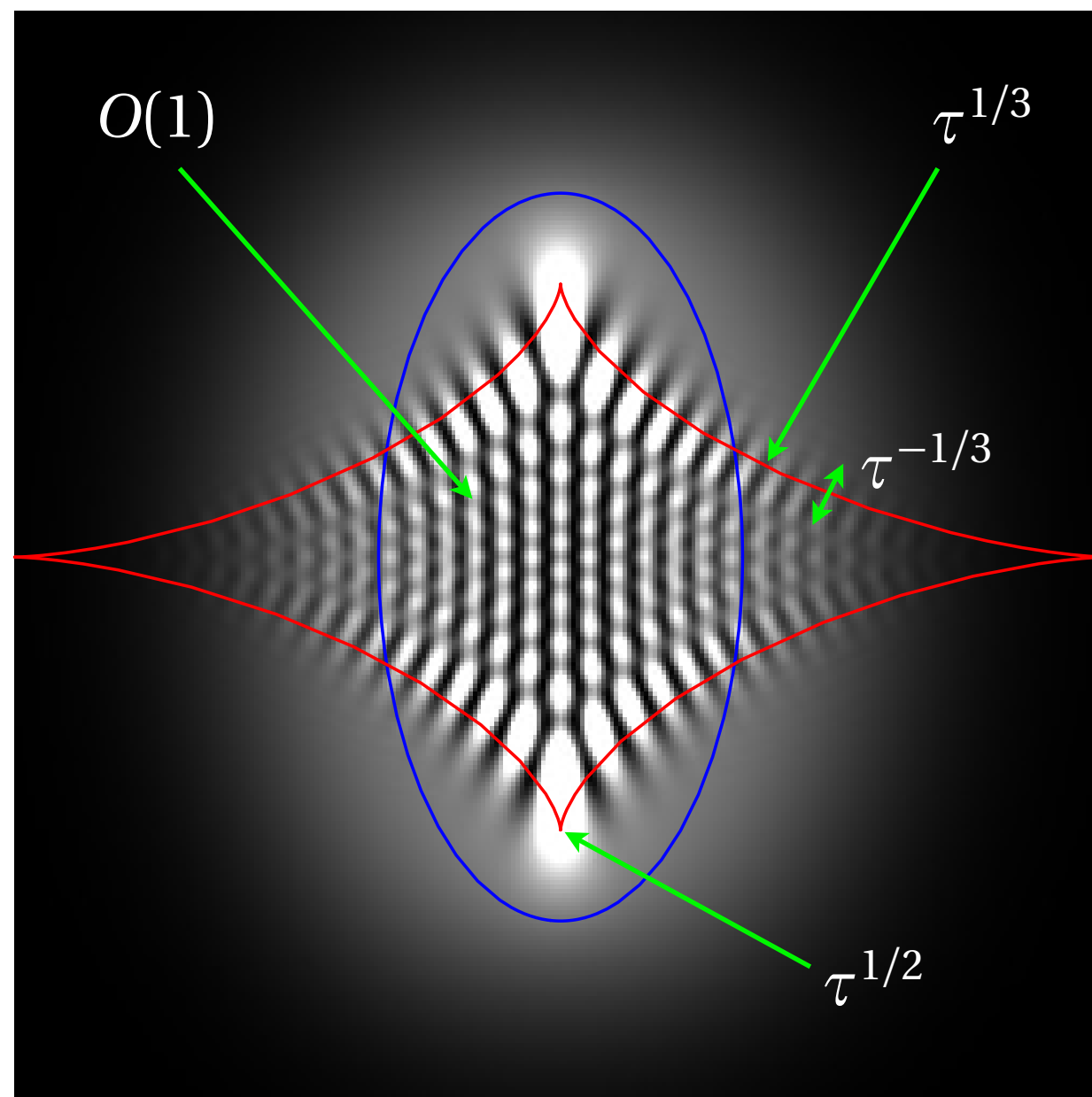
# Other initial shapes? The evolute

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# Scaling of the probability density

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# Computation everywhere

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Even very simple physical processes can solve interesting problems, if they take place in unusual settings

The input to an algorithm can be given in the form of a Hamiltonian, a unitary operator, or an initial state

What other serendipities are still out there?



# Shameless Plug

This book rocks! You somehow manage to combine the fun of a popular book with the intellectual heft of a textbook.

— Scott Aaronson

A treasure trove of information on algorithms and complexity, presented in the most delightful way.

— Vijay Vazirani

A creative, insightful, and accessible introduction to the theory of computing, written with a keen eye toward the frontiers of the field and a vivid enthusiasm for the subject matter.

— Jon Kleinberg

Oxford University Press,  
2011

# THE NATURE *of* COMPUTATION



Cristopher Moore  
Stephan Mertens



# Acknowledgments



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