

# On Lattices, Learning with Errors, Random Linear Codes, and Cryptography

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# Outline

- Introduction to lattices
- Main theorem: a hard learning problem
- Application: a stronger and more efficient public key cryptosystem
- Proof of main theorem
  - Overview
  - Part I: Quantum
  - Part II: Classical

# Lattices

Basis:

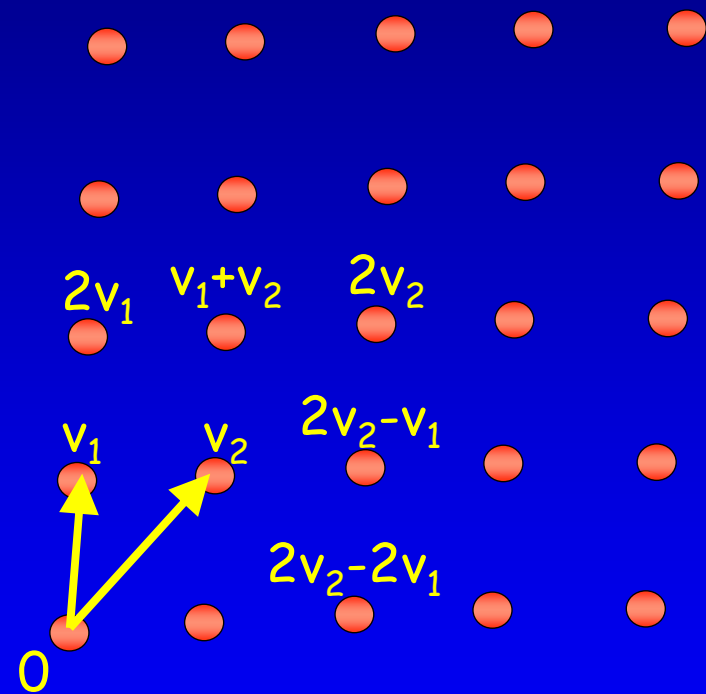
$v_1, \dots, v_n$  vectors in  $\mathbb{R}^n$

The lattice  $L$  is

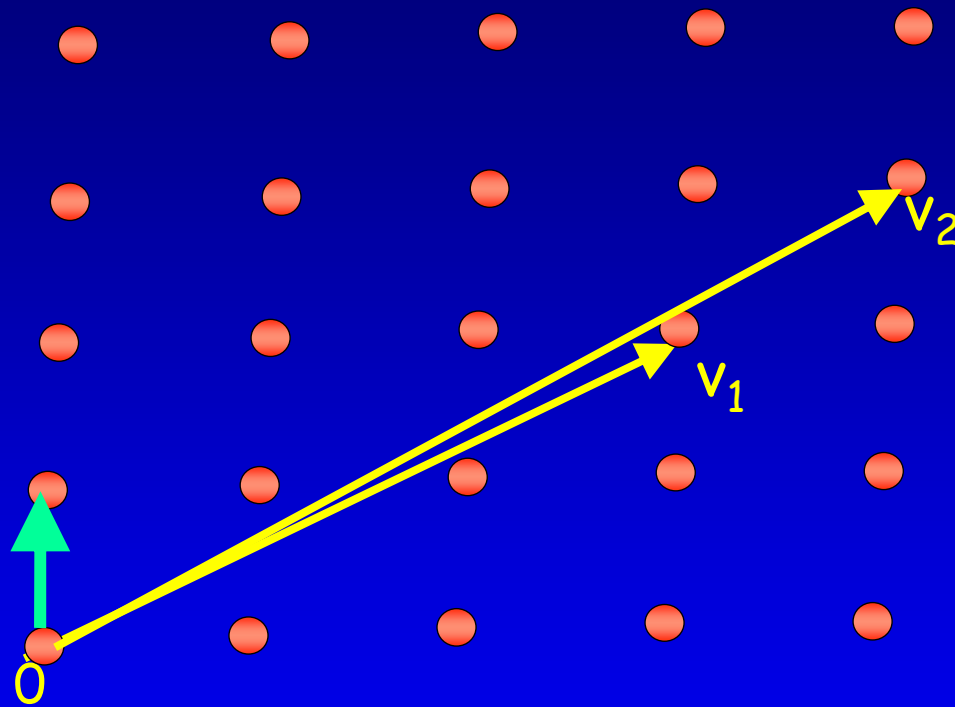
$$L = \{a_1 v_1 + \dots + a_n v_n \mid a_i \text{ integers}\}$$

The dual lattice of  $L$  is

$$L^* = \{x \mid \forall y \in L, \langle x, y \rangle \in \mathbb{Z}\}$$

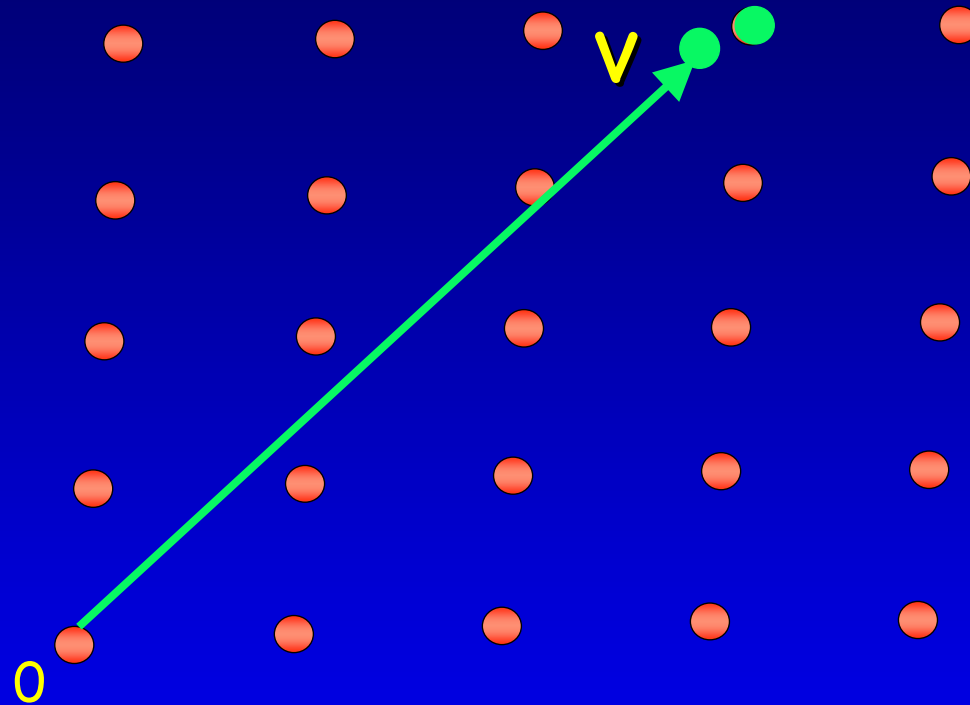


# Shortest Vector Problem (SVP)



- SVP: Given a lattice, find an approximately shortest vector

# Closest Vector Problem ( $CVP_d$ )



- $CVP_d$ : Given a lattice and a target vector within distance  $d$ , find the closest lattice point

**Main Theorem**

**Hardness of Learning**

# Learning from parity with error

- Let  $s \in \mathbb{Z}_2^n$  be a secret
- We have random equations modulo 2 with error (everything independent):

$$\begin{array}{rcl}
 s_2 + s_3 + s_4 + \dots + s_n & \approx & 0 \\
 s_1 + s_2 + \dots + s_4 + \dots + s_n & \approx & 1 \\
 s_1 + \dots + s_3 + s_4 + s_5 + \dots + s_n & \approx & 1 \\
 s_2 + s_3 + s_4 + \dots + s_6 + \dots + s_n & \approx & 0 \\
 \vdots & & 
 \end{array}$$

- Without error, it's easy!

# Learning from parity with error

- More formally, we need to learn  $s$  from samples of the form  $(t, st+e)$  where  $t$  is chosen uniformly from  $\mathbb{Z}_2^n$  and  $e$  is a bit that is 1 with probability 10%.
- Easy algorithms need  $2^{O(n)}$  equations/time
- Best algorithm needs  $2^{O(n/\log n)}$  equations/time [BlumKalaiWasserman'00]
- Open question: why is this problem so hard?



# Learning modulo $p$

- Fix some  $p < \text{poly}(n)$
- Let  $s \in \mathbb{Z}_p^n$  be a secret
- We have random equations modulo  $p$  with error:

$$2s_1 + 0s_2 + 2s_3 + 1s_4 + 2s_5 + 4s_6 + \dots + 4s_n \approx 2$$

$$0s_1 + 1s_2 + 5s_3 + 0s_4 + 6s_5 + 6s_6 + \dots + 2s_n \approx 4$$

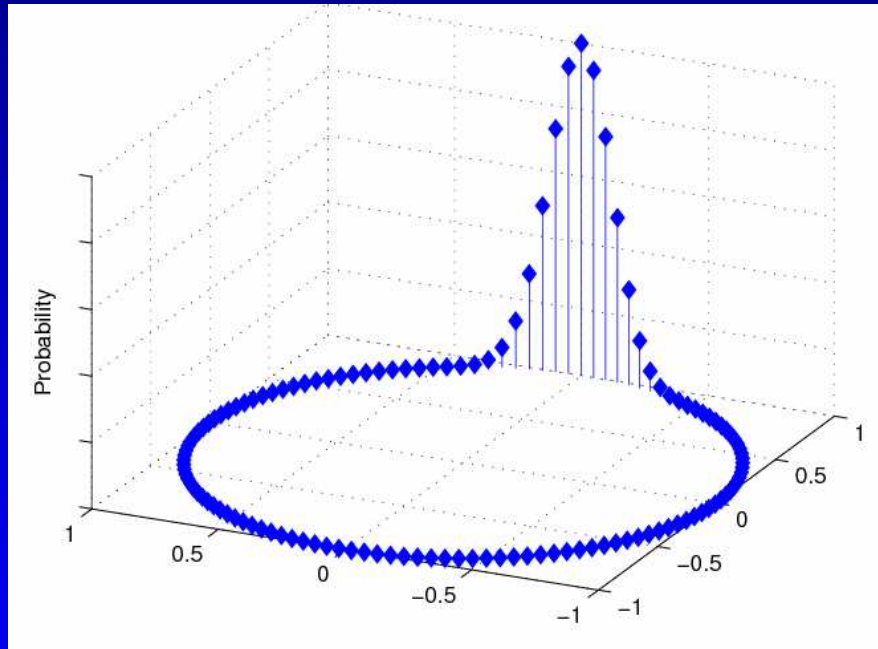
$$6s_1 + 5s_2 + 2s_3 + 0s_4 + 5s_5 + 2s_6 + \dots + 0s_n \approx 2$$

$$6s_1 + 4s_2 + 4s_3 + 4s_4 + 3s_5 + 3s_6 + \dots + 1s_n \approx 5$$

⋮

# Learning modulo $p$

- More formally, we need to learn  $s$  from samples of the form  $(t, st+e)$  where  $t$  is chosen uniformly from  $Z_p^n$  and  $e$  is chosen from  $Z_p$



- Easy algorithms need  $2^{O(n \log n)}$  equations/time
- Best algorithm needs  $2^{O(n)}$  equations/time  
[BlumKalaiWasserman'00]

# Main Theorem

Learning modulo  $p$  is as hard as worst-case lattice problems using a quantum reduction

- In other words: solving the problem implies an efficient quantum algorithm for lattices

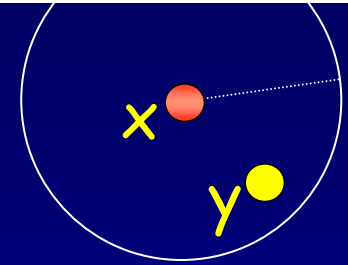
# Equivalent formulation

- For  $m = \text{poly}(n)$ , let  $C$  be a random  $m \times n$  matrix with elements in  $\mathbb{Z}_p$ . Given  $Cs + e$  for some  $s \in \mathbb{Z}_p^n$  and some noise vector  $e \in \mathbb{Z}_p^m$ , recover  $s$ .
- This is the problem of decoding from a random linear code

# Why Quantum?

- As part of the reduction, we need to perform a certain algorithmic task on lattices
- We do not know how to do it classically, only quantumly!

# Why Quantum?



- We are given an oracle that solves  $CVP_d$  for some small  $d$
- As far as I can see, the only way to generate inputs to this oracle is:
  - Somehow choose  $x \in L$
  - Let  $y$  be some random vector within dist  $d$  of  $x$
  - Call the oracle with  $y$
- The answer is  $x$ . But we already know the answer !!
- Quantumly, being able to compute  $x$  from  $y$  is very useful: it allows us to transform the state  $|y, x\rangle$  to the state  $|y, 0\rangle$  reversibly (and then we can apply the quantum Fourier transform)

**Application:**

**New Public Key Encryption Scheme**

# Previous lattice-based PKES

[AjtaiDwork96,GoldreichGoldwasserHalevi97,R'03]

- Main advantages:
  - Based on a lattice problem
  - Worst-case hardness
- Main disadvantages:
  - Based only on unique-SVP
  - Impractical (think of  $n$  as 100):
    - Public key size  $O(n^4)$
    - Encryption expands by  $O(n^2)$



# Ajtai's recent PKES [Ajtai05]

- Main advantages:
  - Practical (think of  $n$  as 100):
    - Public key size  $O(n)$
    - Encryption expands by  $O(n)$
- Main disadvantages:
  - Not based on lattice problem
  - No worst-case hardness

# New lattice-based PKES

[This work]

- Main advantages:

quantum

- Worst-case hardness
- Based on the main lattice problems (SVP, SIVP)
- Practical (think of  $n$  as 100):
  - Public key size  $O(n)$
  - Encryption expands by  $O(n)$
- Breaking the cryptosystem implies an efficient quantum algorithm for lattices
- In fact, security is based on the learning problem (no quantum needed here)

# The Cryptosystem

- Everything modulo 4
- Private key: 4 random numbers

1      2      0      3

- Public key: a 6x4 matrix and approximate inner product

$$\rightarrow 2 \cdot 1 + 0 \cdot 2 + 1 \cdot 0 + 2 \cdot 3 \approx 0$$

$$1 \cdot 1 + 2 \cdot 2 + 2 \cdot 0 + 3 \cdot 3 \approx 2$$

$$0 \cdot 1 + 2 \cdot 2 + 0 \cdot 0 + 3 \cdot 3 \approx 1$$

$$\rightarrow 1 \cdot 1 + 2 \cdot 2 + 0 \cdot 0 + 2 \cdot 3 \approx 0$$

$$0 \cdot 1 + 3 \cdot 2 + 1 \cdot 0 + 3 \cdot 3 \approx 3$$

$$3 \cdot 1 + 3 \cdot 2 + 0 \cdot 0 + 2 \cdot 3 \approx 3$$

- Encrypt the bit 0:

$$3 \cdot ? + 2 \cdot ? + 1 \cdot ? + 0 \cdot ? \approx 1$$

- Encrypt the bit 1:

$$3 \cdot ? + 2 \cdot ? + 1 \cdot ? + 0 \cdot ? \approx 3$$

# **Proof of the Main Theorem**

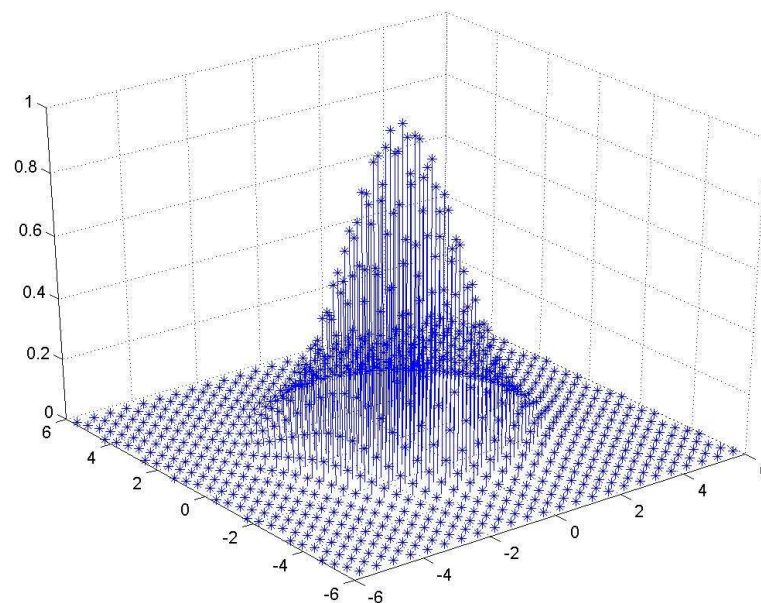
## **Overview**

# Gaussian Distribution

- Define a Gaussian distribution on a lattice (normalization omitted)

$$\forall x \in L, D_r(x) = e^{-\|x/r\|^2}$$

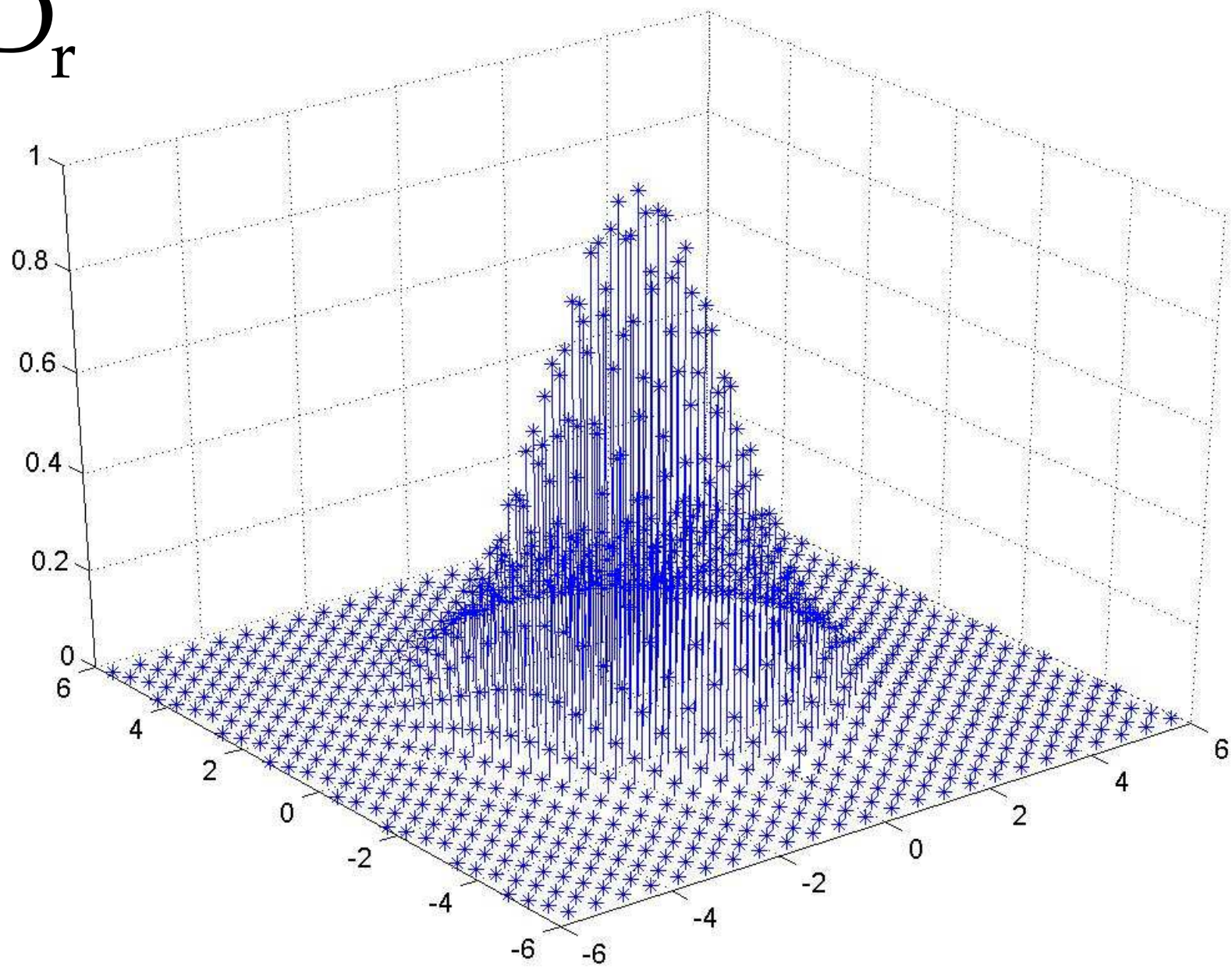
- We can efficiently sample from  $D_r$  for large  $r=2^n$



# The Reduction

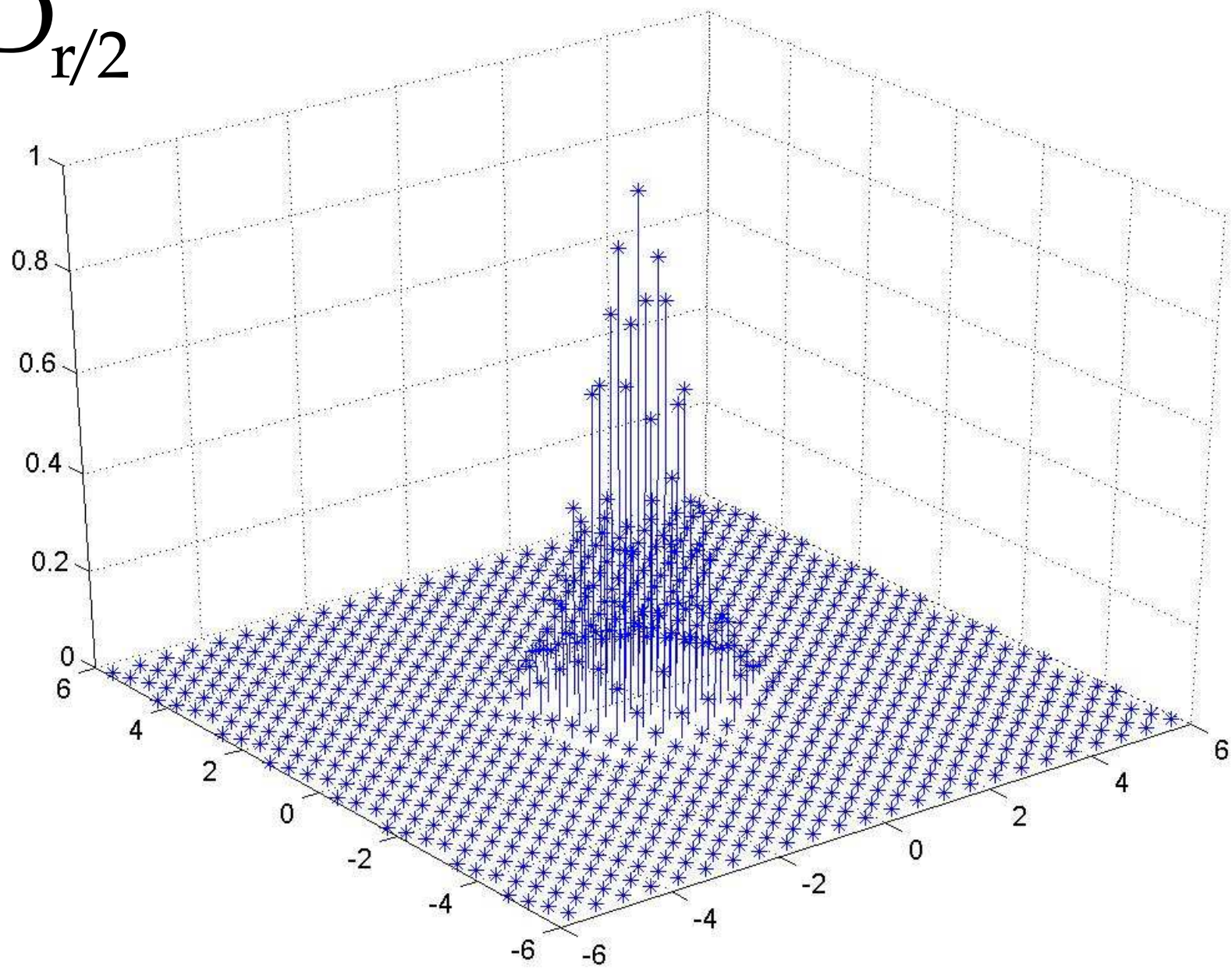
- Assume the existence of an algorithm for the learning modulo  $p$  problem for  $p=2\sqrt{n}$
- Our lattice algorithm:
  - $r=2^n$
  - Take  $\text{poly}(n)$  samples from  $D_r$
  - Repeat:
    - Given  $\text{poly}(n)$  samples from  $D_r$  compute  $\text{poly}(n)$  samples from  $D_{r/2}$
    - Set  $r \leftarrow r/2$
  - When  $r$  is small, output a short vector

$D_r$





$D_{r/2}$





# Obtaining $D_{r/2}$ from $D_r$

$$p=2\sqrt{n}$$

- Lemma 1:

Given  $\text{poly}(n)$  samples from  $D_r$ , and an oracle for 'learning modulo  $p$ ', we can solve

$\text{CVP}_{p/r}$  in  $L^*$

- No quantum here  $J$

- Lemma 2:

Given a solution to  $\text{CVP}_d$  in  $L^*$ , we can obtain samples from  $D_{\sqrt{n}/d}$

- Quantum  $K$
- Based on the quantum Fourier transform

→ Classical, uses learning oracle  
←..... Quantum

Samples from  $D_r$  in  $L$

Solution to  $CVP_{p/r}$  in  $L^*$

Samples from  $D_{r/2}$  in  $L$

Solution to  $CVP_{2p/r}$  in  $L^*$

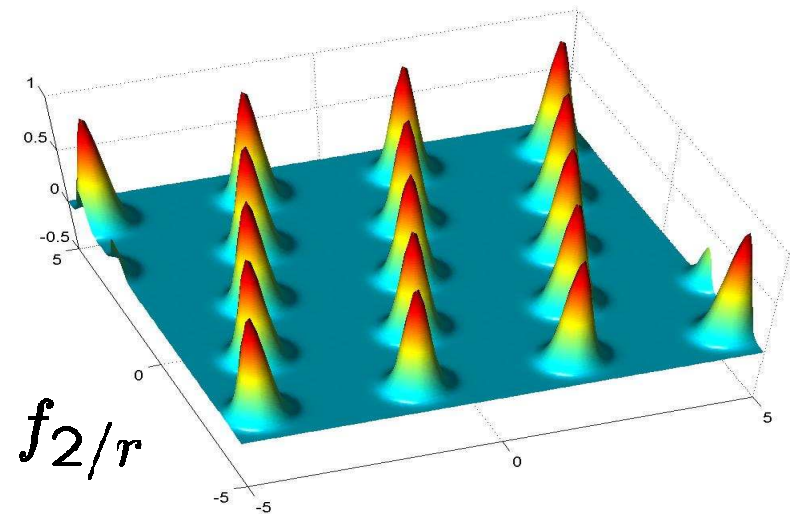
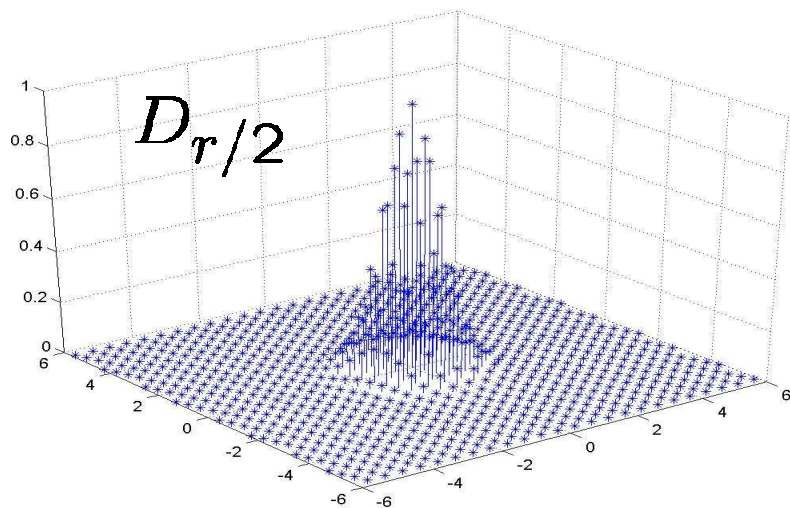
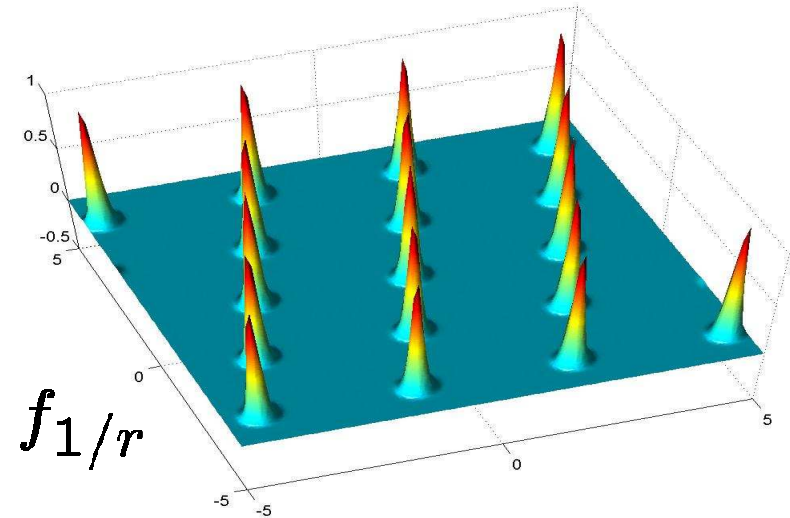
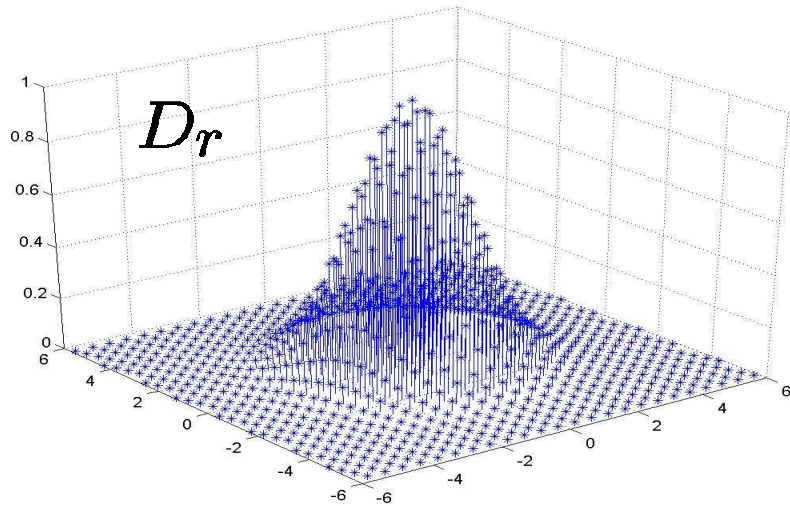
Samples from  $D_{r/4}$  in  $L$

Solution to  $CVP_{4p/r}$  in  $L^*$

# Fourier Transform

Primal world ( $L$ )

Dual world ( $L^*$ )



# Fourier Transform

- The Fourier transform of  $D_r$  is given by

$$f_{1/r}(x) \approx e^{-\|r \cdot \text{dist}(x, L^*)\|^2}$$

- Its value is
  - 1 for  $x$  in  $L^*$ ,
  - $e^{-1}$  at points of distance  $1/r$  from  $L^*$ ,
  - $1/40$  at points far away from  $L^*$ .

# **Proof of the Main Theorem**

**Lemma 2: Obtaining  $D_{\sqrt{n}/d}$  from  $CVP_d$**

# From $CVP_d$ to $D_{\sqrt{n}/d}$

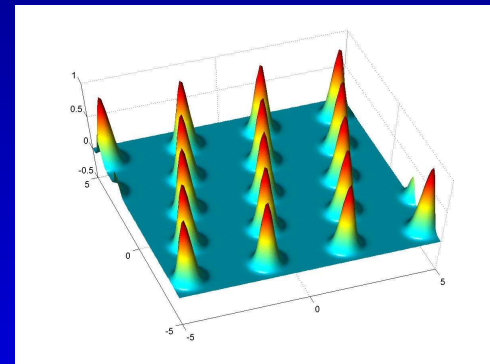
- Assume we can solve  $CVP_d$ ; we'll show how to obtain samples from  $D_{\sqrt{n}/d}$

- Step 1:

Create the quantum state

$$\sum_{x \in \mathbb{R}^n} f_{d/\sqrt{n}}(x) |x\rangle$$

by adding a Gaussian to each lattice point and uncomputing the lattice point by using the  $CVP$  algorithm



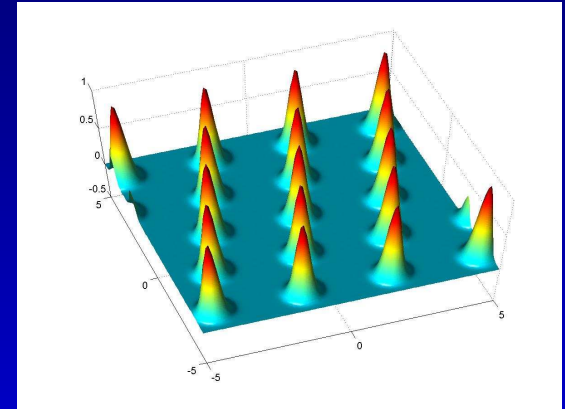
# From $CVP_d$ to $D_{\sqrt{n}/d}$

- Step 2:

Compute the quantum Fourier transform of

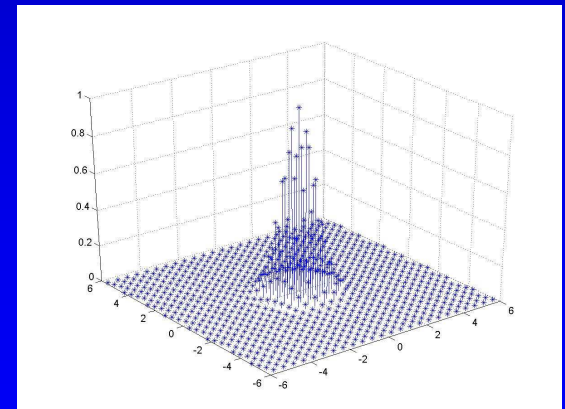
$$\sum_{x \in \mathbb{R}^n} f_{d/\sqrt{n}}(x) |x\rangle$$

It is exactly  $D_{\sqrt{n}/d}$  !!



- Step 3:

Measure and obtain one sample from  $D_{\sqrt{n}/d}$



- By repeating this process, we can obtain  $\text{poly}(n)$  samples

# From $CVP_d$ to $D_{\sqrt{n}/d}$

- More precisely, create the state  $\sum_{y \in L^*} |y\rangle$

- And the state  $\sum_{x \in \mathbb{R}^n} e^{-\|(\sqrt{n}/d)x\|^2} |x\rangle$

- Tensor them together and add first to second

$$\sum_{y \in L^*, x \in \mathbb{R}^n} e^{-\|(\sqrt{n}/d)x\|^2} |y, x + y\rangle$$

- Uncompute first register by solving  $CVP_{p/r}$

$$\sum_{x \in \mathbb{R}^n} e^{-\|(\sqrt{n}/d) \cdot \text{dist}(x, L^*)\|^2} |x\rangle \approx \sum_{x \in \mathbb{R}^n} f_{d/\sqrt{n}}(x) |x\rangle$$



# **Proof of the Main Theorem**

**Lemma 1: Solving  $\text{CVP}_{p/r}$  given  
samples from  $D_r$  and an oracle for  
learning mod  $p$**

# It's enough to approximate $f_{p/r}$

- Lemma: being able to approximate  $f_{p/r}$  implies a solution to  $CVP_{p/r}$
- Proof Idea - walk uphill:
  - $f_{p/r}(x) > \frac{1}{4}$  for points  $x$  of distance  $< p/r$
  - Keep making small modifications to  $x$  as long as  $f_{p/r}(x)$  increases
  - Stop when  $f_{p/r}(x) = 1$  (then we are on a lattice point)

# What's ahead in this part

- For warm-up, we show how to approximate  $f_{1/r}$  given samples from  $D_r$ 
  - No need for learning
  - This is main idea in [AharonovR'04]
- Then we show how to approximate  $f_{2/r}$  given samples from  $D_r$  and an oracle for the learning problem
- Approximating  $f_{p/r}$  is similar

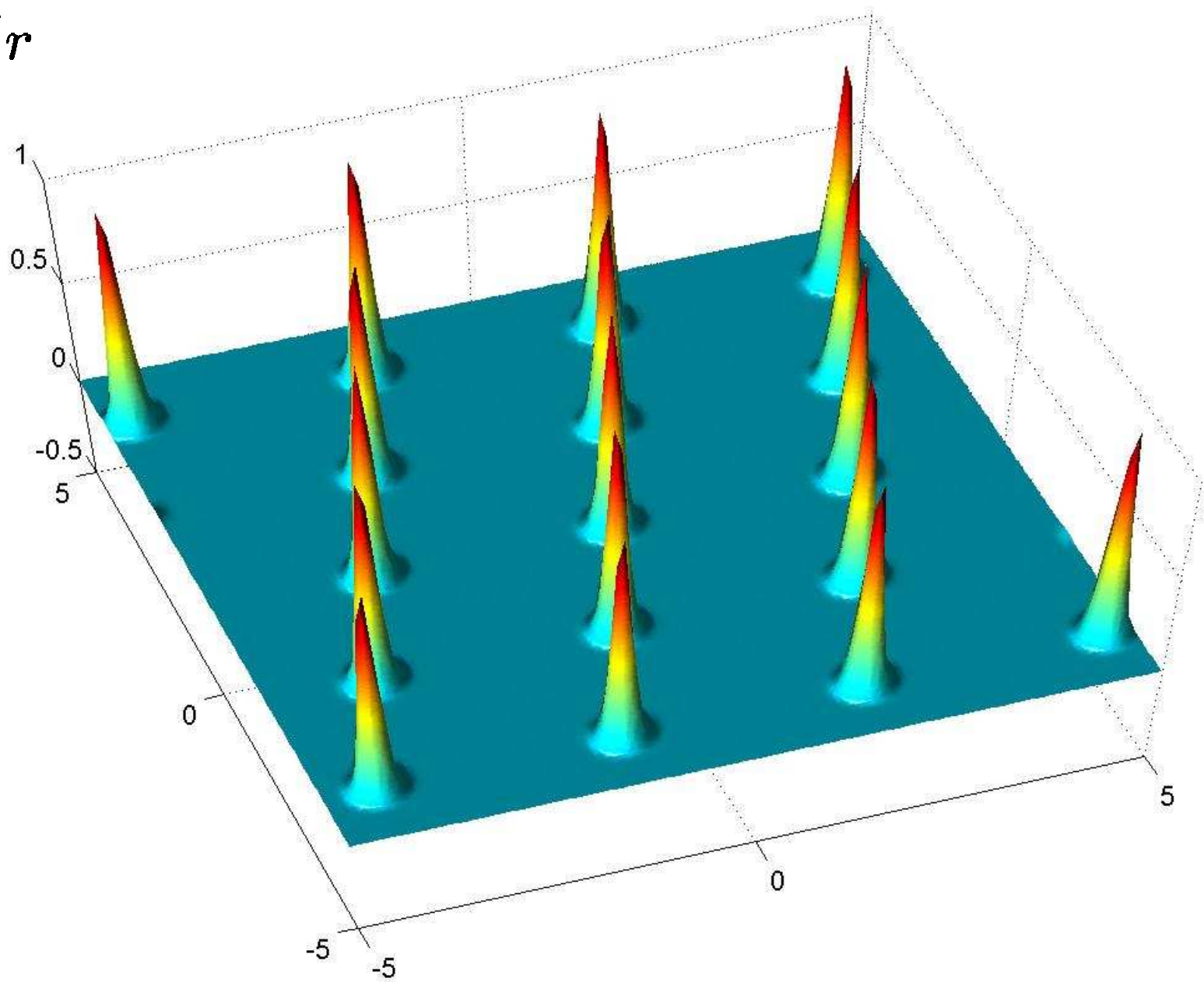
# Warm-up: approximating $f_{1/r}$

- Let's write  $f_{1/r}$  in its Fourier representation:

$$\begin{aligned} f_{1/r}(x) &= \sum_{w \in L} \widehat{f_{1/r}}(w) \cos(2\pi \langle w, x \rangle) \\ &= \sum_{w \in L} D_r(w) \cos(2\pi \langle w, x \rangle) \\ &= E_{w \sim D_r} [\cos(2\pi \langle w, x \rangle)] \end{aligned}$$

- Using samples from  $D_r$ , we can compute a good approximation to  $f_{1/r}$  (this is the main idea in [AharonovR'04])

$f_{1/r}$



# Fourier Transform

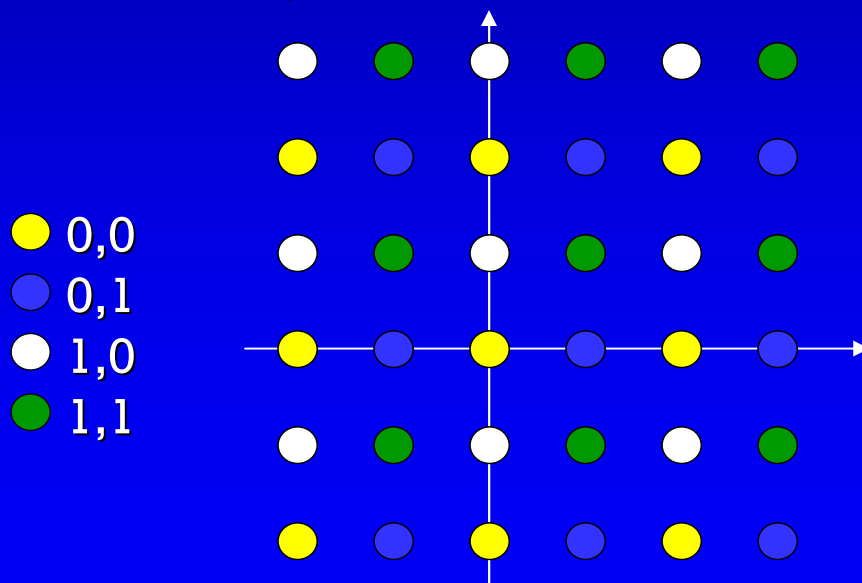
- Consider the Fourier representation again:

$$f_{1/r}(x) = E_{w \sim D_r} [\cos(2\pi \langle w, x \rangle)]$$

- For  $x \in L^*$ ,  $\langle w, x \rangle$  is integer for all  $w$  in  $L$  and therefore we get  $f_{1/r}(x)=1$
- For  $x$  that is close to  $L^*$ ,  $\langle w, x \rangle$  is distributed around an integer. Its standard deviation can be (say) 1.

# Approximating $f_{2/r}$

- Main idea: partition  $D_r$  into  $2^n$  distributions
- For  $t \in (\mathbb{Z}_2)^n$ , denote the translate  $t$  by  $D_r^t$
- Given a lattice point we can compute its  $t$
- The probability on  $(\mathbb{Z}_2)^n$  obtained by sampling from  $D_r$  and outputting  $t$  is close to uniform



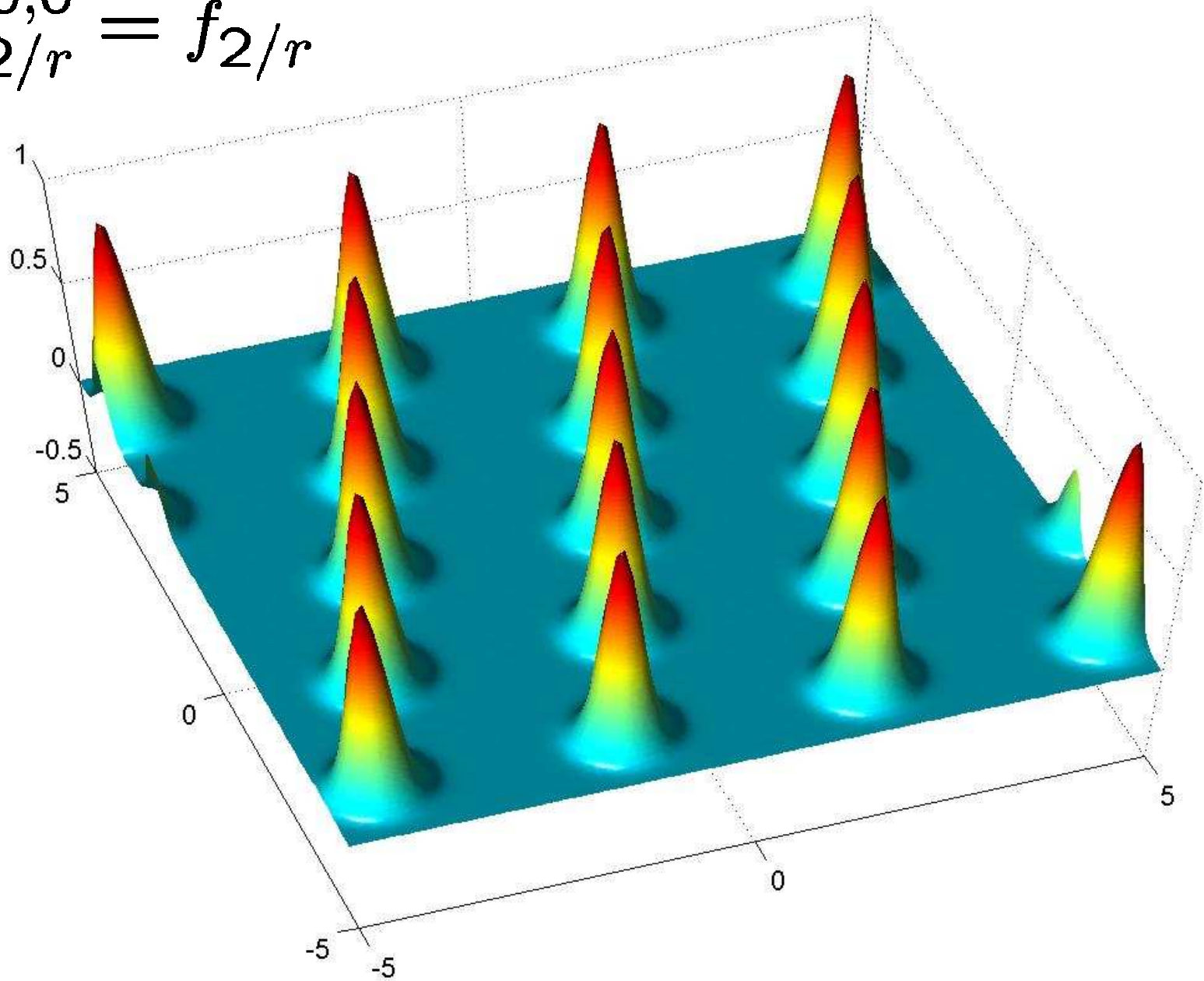
# Approximating $f_{2/r}$

- Hence, by using samples from  $D_r$  we can produce samples from the following distribution on pairs  $(t, w)$ :
  - Sample  $t \in (\mathbb{Z}_2)^n$  uniformly at random
  - Sample  $w$  from  $D_r^t$
- Consider the Fourier transform of  $D_r^t$

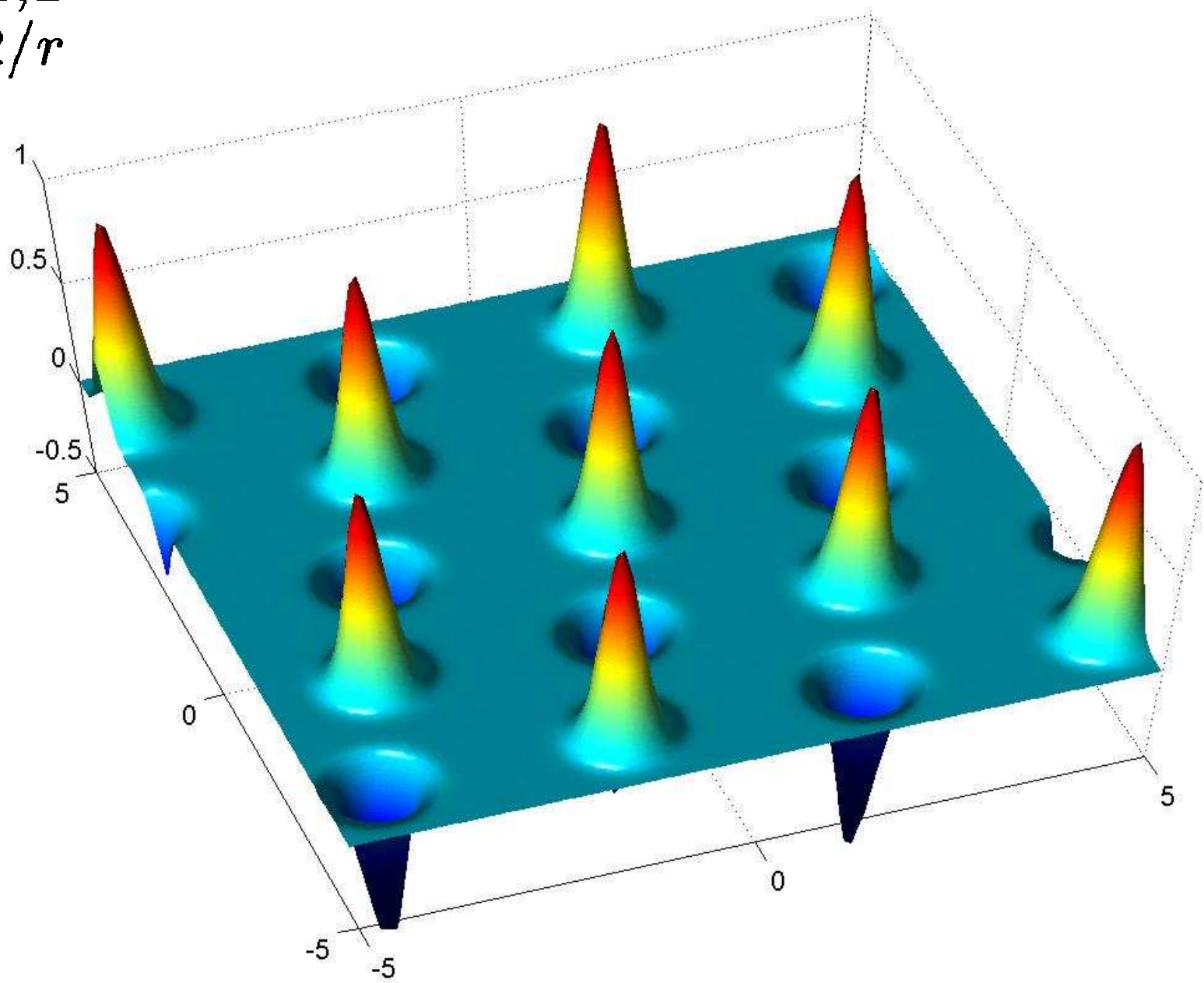
$$f_{2/r}^t(x) = E_{w \sim D_r^t} [\cos(\pi \langle w, x \rangle)]$$



$$f_{2/r}^{0,0} = f_{2/r}$$



$$f_{2/r}^{1,1}$$



# Approximating $f_{2/r}$

- The functions  $f_{2/r}^t$  look almost like  $f_{2/r}$
- Only difference is that some Gaussians have their sign flipped
- Approximating  $f_{2/r}^t$  is enough: we can easily take the absolute value and obtain  $f_{2/r}$
- For this, however, we need to obtain several pairs  $(t,w)$  for the same  $t$
- The problem is that each sample  $(t,w)$  has a different  $t$  !

# Approximating $f_{2/r}$

- Fix  $x$  close to  $L^*$
- The sign of its Gaussian is  $\pm 1$  depending on  $\langle s, t \rangle \bmod 2$  for  $s \in (\mathbb{Z}_2)^n$  that depends only on  $x$
- The distribution of  $\langle x, w \rangle \bmod 2$  when  $w$  is sampled from  $D_r^\dagger$  is centred around  $\langle s, t \rangle \bmod 2$
- Hence, we obtain equations modulo 2 with error:

$$\langle s, t \rangle \pm \frac{1}{4} \langle x, w_1 \rangle \bmod 2$$

$$\langle s, t \rangle \pm \frac{1}{4} \langle x, w_2 \rangle \bmod 2$$

$$\langle s, t \rangle \pm \frac{1}{4} \langle x, w_3 \rangle \bmod 2$$

$\vdots$

# Approximating $f_{2/r}$

- Using the learning algorithm, we solve these equations and obtain  $s$
- Knowing  $s$ , we can cancel the sign
- Averaging over enough samples gives us an approximation to  $f_{2/r}$

# Open Problems 1/4

- Dequantize the reduction:
  - This would lead to the 'ultimate' lattice-based cryptosystem (based on SVP, efficient)
  - Main obstacle: what can one do classically with a solution to  $CVP_d$ ?
- Construct even more efficient schemes based on special classes of lattices such as cyclic lattices
  - For hash functions this was done by Micciancio

# Open Problems 2/4

- Extend to learning from parity (i.e.,  $p=2$ ) or even some constant  $p$ 
  - Is there something inherently different about the case of constant  $p$ ?
- Use the 'learning mod  $p$ ' problem to derive other lattice-based hardness results
  - Recently, used by Klivans and Sherstov to derive hardness of learning problems

# Open Problems 3/4

- Cryptanalysis
  - Current attacks limited to low dimension [NguyenStern98]
  - New systems [Ajtai05,R05] are efficient and can be easily used with dimension 100+
- Security against chosen-ciphertext attacks
  - Known lattice-based cryptosystems are not secure against CCA



# Open Problems 4/4

- Comparison with number theoretic cryptography
  - E.g., can one factor integers using an oracle for  $n$ -approximate SVP?
- Signature schemes
  - Can one construct provably secure lattice-based signature schemes?