# Hard Instances of Lattice Problems Average Case - Worst Case Connections 

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## Outline

Abstract

Lattices

The Random Class

Worst-Case - Average-Case Connection

## Abstract

## Hard Problems Already Exist

## All Time Classic Hard Problems

- NP-Complete problems
- Factorization
- Discrete Logarithm
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## Worst-Case Hardness

Those problems are hard only under certain distributions. Often it is not clear how to find such a distribution.

## One Step Further

## Worst-Case Vs. Average-Case Hardness

A random class of lattices so that if the SVP is easy to solve then the above problems are easy in every lattice.

## Lattice Definition

## Definition

Let $B \in \mathbb{R}^{m \times n}$, we consider the set
$\mathcal{L}=\left\{y: y=B \cdot x \quad \forall x \in \mathbb{Z}^{1 \times n}\right\}$, that is the set of all integer linear combinations of $B$. We call every $\mathcal{L}$ with the above properties a lattice.

## Lattices



Figure: An example of a lattice and its basis.

## Lattices



Figure: A lattice has more than one bases.

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- Infinite (countable) different bases.
- The only part of a lattice that is known is the place where the basis vectors lie.


## Fundamental Parallelepiped

## Definition

Let $\mathcal{L}$ be a lattice, and let a basis for $\mathcal{L}$ is $B=\left[b_{1}, \ldots, b_{n}\right]$, $b_{i}$ are the column vectors of $B$, then we define the set
$\mathcal{P}(B)=\left\{y: y=\sum_{i=0}^{n} x_{i} \cdot b_{i}, \quad x_{i} \in\left[-\frac{1}{2}, \frac{1}{2}\right)\right\}$. We call $\mathcal{P}(B)$ the
fundamental parallelepiped of $\mathcal{L}$ with respect to the basis $B$.

## Mathematical Tools

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- Efficiently computable distinguished representatives as $t-B \cdot\left\lceil B^{-1} \cdot t\right]$.
- Partition of the space $\mathbb{R}^{n}$ by multiplies of fundamental parallelepiped.


## Lattice Problems \& Solutions

## Classic Hard Problems

P1 approximate SVP
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## Classic Algorithms and Bounds

- LLL Reduction Algorithm ( $2^{\frac{n-1}{2}} \operatorname{sh}(\mathcal{L})$ approximation).
- Babai's Nearest Plane Algorithm.


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Bounds

- Shor proved that in LLL the approximation factor can be replaced by $(1+\epsilon)^{n}$.
$\searrow$ Minkowski (Convex Body Theorems) $\operatorname{sh}(\mathcal{L}) \leq c \sqrt{n} \operatorname{det}(\mathcal{L})^{\frac{1}{n}}$


## More on Lattices...

## Definition (Dual Lattice)

Let $\mathcal{L}$ be a lattice, we define the dual lattice to be the set $\mathcal{L}^{*}=\{y: \forall x \in \mathcal{L}\langle x, y\rangle \in \mathbb{Z}\}$.

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## Definition (Smoothing Parameter)

For any $n$-dimensional lattice $\mathcal{L}$ and $\epsilon \in \mathbb{R}^{+}$, we define its smoothing parameter $\eta_{\epsilon}(\mathcal{L})$ to be the smallest $s$ such that $\rho_{1 / s}\left(\mathcal{L}^{*} \backslash\{0\}\right) \leq \epsilon$.

## Sampling

## Lemma

For any $s>0, c \in \mathbb{R}^{n}$ and lattice $\mathcal{L}(B)$, the statistical distance between $D_{s, c} \bmod \mathcal{P}(B)$ and the uniform distribution over $\mathcal{P}(B)$ is at most $\frac{1}{2} \rho_{1 / s}\left(\mathcal{L}(B)^{*} \backslash\{0\}\right)$. In particular, for any $\epsilon>0$ and any $s \geq \eta_{\epsilon}(B)$, holds that
$\Delta\left(D_{s, c} \bmod \mathcal{P}(B), U(\mathcal{P}(B))\right) \leq \epsilon / 2$

## The Random Class

## Definition of $\mathcal{L}$ and $\wedge$

1. $\mathcal{L}: q$-ary lattice.
2. $\wedge$ : the perpendicular lattice of $\mathcal{L}$.

## Definition of $\mathcal{L}$ and $\wedge$

## Symbols

$\triangleright B=\left(u_{1}: u_{2}: \ldots: u_{m}\right), u_{i} \in \mathbb{Z}^{n}$.

- Lattice: $\mathcal{L}(B, q)=\left\{y: y=B \cdot x \bmod q, \forall x \in \mathbb{Z}^{1 \times m}\right\}$ $\left(\mathcal{L}(B, q) \subseteq \mathbb{Z}^{n}\right)$.
> Perpendicular Lattice: $\wedge(B, q)=\{y: y \cdot B \equiv 0 \bmod q\}$ $\left(\wedge(B, q) \subseteq \mathbb{Z}^{n}\right)$.

Parameters
$>m=\left[c_{1} n \log n\right]$
$>q=\left[n^{c_{2}}\right]$

## Our Goal

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1. Redefine the basis $B$ so that if there is a PT algorithm that finds a shortest vector in $\wedge$ then it breaks P1, P2, P3 in any lattice.

## First Step

## Substitute $B$ by $\lambda^{\prime}$

Define $\lambda^{\prime}=\left(v_{1}, \ldots, v_{m}\right), v_{i} \in \mathbb{Z}_{q}^{n}$. Every $v_{i}$ is chosen independently and with uniform distribution from the set of all vectors in $\mathbb{Z}_{q}^{n}$.

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The problem of finding a SV in $\Lambda\left(\lambda^{\prime}, q\right)$ is equivalent to solve a linear simultaneous Diophantine equation.

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Theorem (Dirichlet)
If $c_{1}$ is sufficiently large with respect to $c_{2}$ then there is always a SV in $\wedge\left(\lambda^{\prime}, q\right)$ which is sorter than $n$.

## $\Lambda\left(\lambda^{\prime}, q\right)$ is Unknown to Everybody (Crypto Only)

It seems that there is no way of constructing a shortest vector in $\Lambda\left(\lambda^{\prime}, q\right)$. So we don't have a trapdoor!

## Second Step

## Substitute $\lambda^{\prime}$ by

Define $\lambda=\left(v_{1}, \ldots, v_{m}\right), \forall i \in\{1, \ldots, m-1\} v_{i} \in \mathbb{Z}_{q}^{n}$ also $v_{i}$ is chosen independently and with uniform distribution from the set of all vectors in $\mathbb{Z}_{q}^{n}$. We also define $v_{m}=-\sum_{i=1}^{m-1} \delta_{i} v_{i}$. Where $\delta_{i}$ is a, randomly generated, sequence of 0 and 1 's.

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## No Loss of Generality

The distribution of $\lambda$ is exponentially close to the uniform distribution. $\sum_{x \in A}\left|P(\lambda=x)-\frac{1}{A}\right| \leq \frac{1}{2^{c n}}$, where $A$ is the set of all possible values of $\lambda$.

# Worst-Case - Average-Case Connection 

## Main Theorem

Theorem
There are absolute constants $c_{1}, c_{2}, c_{3}$ so that the following holds:
Suppose that there is a PPT algorithm $\mathcal{A}$ which given a value of the random variable $\lambda_{n, c_{1}, c_{2}}$ as an input, with a probability of at least $\frac{1}{2}$ outputs a nonzero vector of $\Lambda\left(\lambda_{n, c_{1}, c_{2}},\left[n^{c_{1}}\right]\right)$ of length at most $n$.
Then, there is a PPT algorithm $\mathcal{B}$ with the following properties: If the linearly independent vectors $a_{1}, \ldots, a_{n} \in \mathbb{Z}^{n}$ are given as an input then in polynomial time in $\sum \operatorname{size}\left(a_{i}\right)$ gives the output $\left(d_{1}, \ldots, d_{n}\right)$ so that with probability of greater than $1-\frac{1}{2^{-\sum \operatorname{size}\left(a_{i}\right)}}$ $\left(d_{1}, \ldots, d_{n}\right)$ is a basis with $\max \left\|d_{i}\right\| \leq n^{c_{3}} \operatorname{bl}(\mathcal{L})$

## Main Tool for the Proof

## Easy Construction of a Basis

There is a polynomial time algorithm that from a set of $n$ linearly independent vectors $r_{1}, \ldots, r_{n} \in \mathcal{L}$ can construct a basis $s_{1}, \ldots, s_{n}$ of $\mathcal{L}$ so that $\max \left\|s_{i}\right\| \leq n \max \left\|r_{i}\right\|$

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## Defining a new Goal

Construct a set of $n$ linearly independent vectors of $\mathcal{L}$ so that each of them is shorter than $n^{c_{3}-1} b l(\mathcal{L})$.

## Proof of Main Theorem

## Assume that we have the set of linearly independent vectors $a_{1}, \ldots, a_{n} \in \mathcal{L}$. Let $M=\max \left\|a_{i}\right\|$

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First Case (Trivial)
If $M \leq n^{c_{3}-1} b /(\mathcal{L})$ we are done.

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## Second Case (Hmmm...)

If $M>n^{c_{3}-1} b l(\mathcal{L})$ we construct (?) a set of linearly independent vectors of $b_{1}, \ldots, b_{n} \in \mathcal{L}$ so that $\max \left\|b_{i}\right\| \leq \frac{M}{2}$. Then we repeat the algorithm with input the set $b_{1}, \ldots, b_{n}$.
After $\log _{2} M \leq 2 \sum \operatorname{size}\left(a_{i}\right)$ steps we get a set of linearly independent vectors where each of them is shorter than $n^{c_{3}-1} b l(\mathcal{L})$.

## $\max \left\|b_{i}\right\| \leq \frac{M}{2}$

1. Starting from the set $a_{1}, \ldots, a_{n} \in \mathcal{L}$ we construct a set of linearly independent vectors $f_{1}, \ldots, f_{n} \in \mathcal{L}$ so that $\max \left\|f_{i}\right\| \leq n^{3} M$ and also the parallelepiped $W=\mathcal{P}\left(f_{1}, \ldots, f_{n}\right)$ is very close to a cube.
2. We cut $W$ into $q^{n}$ parallelepipeds each of the form $\sum \frac{t_{i}}{q} f_{i}+\frac{1}{q} W$, where $0 \leq t_{i}<q$ is a sequence of integers.
3. We take a random sequence of lattice points
$\xi_{1}, \ldots, \xi_{m}, m=\left\lfloor c_{1} n \log n\right\rfloor$ from $W$. Let $\xi_{j} \in \sum \frac{t_{i}^{(j)}}{q} f_{i}+\frac{1}{q} W$ then we define $v_{j}=\left(t_{1}^{(j)}, \ldots, t_{n}^{(j)}\right)$.
4. Apply $\mathcal{A}$ to the input $\lambda^{\prime}=\left(v_{1}, \ldots, v_{m}\right)$ and get a vector $\left(h_{1}, \ldots, h_{m}\right) \in \mathbb{Z}^{n}$.
5. Then the vector $\sum h_{j}\left(\xi_{j}-\eta_{j}\right) \in \mathcal{L}$ and its length is at most $\frac{M}{2}$, where $\eta_{j}=\sum \frac{t_{j}^{(j)}}{q} f_{j}$.

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## Thank you!!!

