## Lattice Basis Reduction

Bounds and Algorithms

GCD

$$
\operatorname{gcd}(a, b)=\min ^{+}\{|x \cdot a+y \cdot b|: x, y \in \mathbb{Z}\}
$$

* GCD is the minimum nonzero element of a discrete set
* Euclidean algorithm computes this by iteratively subtracting $a$ and $b$ from each other


## A Generalized GCD

$$
\begin{gathered}
B=\left(\begin{array}{ccc}
b_{11} & \cdots & b_{1 n} \\
\vdots & \ddots & \vdots \\
b_{n 1} & \cdots & b_{n n}
\end{array}\right) \\
\lambda(B)=\min ^{+}\left\{\|B \cdot x\|: x \in \mathbb{Z}^{n}\right\}
\end{gathered}
$$

* The set $\left\{B \cdot x: x \in \mathbb{Z}^{n}\right\}$ is called a lattice
* Computing $\lambda(B)$ is NP-hard
* Approximation is active field of research
$\diamond$ NP-hard to approximate to a constant [Micciancio '98, Ajtai '98].
$\diamond$ Polynomial-time algorithms to find a reduced basis that approximates the shortest vector to $(1+\epsilon)^{n}$ [LLL '82, Schnorr '87]


## Lattice Applications

* Direct application
$\diamond$ Knapsack cryptosystems
$\diamond$ Integer programming with a fixed number of variables
* Linear approximation of nonlinear systems
$\diamond$ Small roots of modular polynomials
$\diamond$ Truncated linear congruential generators
* Number theory
$\diamond$ Factoring integer polynomials
$\diamond$ Small integer relations


## Applications of Lattice Basis Reduction

* [Shamir '82] used fixed-dimension IP algorithm [Lenstra '83] based on LLL to break Merkle-Hellman Knapsack cryptosystem ['78].
* The Chor-Rivest Subset Sum cryptosystem ['84] was broken in dimension 103 [Schnorr, Horner '95], using low-density subset sum lattices (suggested dimension is $\sim 200$ ).
* Low-density subset sum can be solved up to density $0.9408 \ldots$
* Other classic applications: Factoring polynomials over $\mathbb{Z}$, finding small integer relations, attacking low-degree RSA, breaking truncated linear congruential pseudo-random number generators, bounding bits leaked by RSA.



A Symmetric Convex Body in a Lattice


How big can $C$ be before containing a lattice point (other than the origin)?

A Tricky Symmetric Convex Body in a Lattice


Minkowski's Convex Body Theorem


Any convex body symmetric about the origin in $\mathbb{R}^{n}$ with volume greater than $2^{n}$, contains a nonzero point of $\mathbb{Z}^{n}$

## Blichfeldt's Lemma

$\bullet$
$\bullet$
$\bullet$
$\bullet$
-
$\square$


Let $\mathcal{M}$ be any bounded open set with volume $>1$. Then $\mathcal{M}$ contains two points $x$ and $y$ with $x-y \in \mathbb{Z}^{n}$

Proof of Blichfeldt's Lemma

## Step 1



* Divide $\mathcal{M}$ based on unit squares

Proof of Blichfeldt's Lemma

## Step 2



* As volume $>1$, two regions must overlap

Proof of Blichfeldt's Lemma

## Step 3



* The overlap points differ by a vector in $\mathbb{Z}^{n} \quad \square$

Minkowski's Convex Body Theorem

Any convex body symmetric about the origin in $\mathbb{R}^{n}$ with volume greater than $2^{n}$, contains a nonzero point of $\mathbb{Z}^{n}$


* Shrink $C$ by factor of 2 in every direction
* Resulting volume $>1$, so Blichfeldt's lemma applies

Minkowski's Convex Body Theorem

$\star x-y \in \mathbb{Z}^{n}$
$\star 2 x, 2 y,-2 y \in C$ as factor of 2 larger and symmetric

Minkowski's Convex Body Theorem

$\star 2 x,-2 y \in C$ as factor of 2 larger and symmetric

* The midpoint $z$ of $2 x$ and $-2 y$ also in $C$ as convex
$\star z=\frac{1}{2}(2 x-2 y)=x-y \in \mathbb{Z}^{n}$


## General Lattices

Any lattice $\mathcal{L}$ is a linear transformation $B$ of $\mathbb{Z}^{n}$


General Lattices


Any (convex, symmetric) body in $\mathcal{L}$ is related to a (convex, symmetric) body in $\mathbb{Z}^{n}$

## Using Minkowski's First Theorem



* The sphere in $\mathcal{L}$ just containing a shortest vector has volume $\lambda(\mathcal{L})^{n} \cdot V_{n}$
* Minkowski's Theorem says



## Using Minkowski's First Theorem


volume of sphere $\quad \lambda(\underset{\sim}{\mathcal{L}})^{n} \cdot V_{n} / \operatorname{det} B \leq 2^{n}$

* Rearranging,

$$
\lambda(\mathcal{L}) \leq 2\left(\operatorname{det}(B) / V_{n}\right)^{1 / n} \leq \sqrt{n} \operatorname{det}(B)^{1 / n}
$$

Outline

1. Elementary bounds $\sqrt{ }$
2. Reduction algorithms
3. (My) current research


Why $B$ is a Basis


The triangle spanned by $B$ contains no lattice points except the vertices

Basis


There are many bases for the same lattice

Why the Bases are the Same


* The red basis can be expressed in the green basis, and vice-versa
* Integer unimodular transformation $U$ with

$$
A=U B
$$

We Like Some Bases Better Than Others


Transform given basis to one with short vectors:

## Basis Reduction

Geometry of Determinant


## Results on Shortest Vectors

* Recall that $\lambda(\mathcal{L})$ is the length of a shortest non-zero vector of $\mathcal{L}$.
* Theory tells us:

$$
\lambda(\mathcal{L}) \leq \sqrt{n} \cdot d(\mathcal{L})^{1 / n}
$$

[Minkowski 1896]

* Polynomial-time LLL algorithm finds $v \in \mathcal{L}$ with:

$$
\begin{aligned}
& |v| \leq 2^{n / 4} \cdot d(\mathcal{L})^{1 / n} \\
& |v| \leq 2^{n / 2} \cdot \lambda(\mathcal{L})
\end{aligned}
$$

[Lenstra, Lenstra, Lovasz '82]

* Block Korkine-Zolotareff reduction replaces 2 with $(1+\epsilon)$

Outline

1. Elementary bounds $\sqrt{ }$
2. Reduction algorithms

* 2-D Gaussian reduction
* LLL reduction
* Block Korkine-Zolotareff reduction

3. (My) current research

2D Reduction

## The Two-Dimensional Case


$b_{1}^{\prime}$ is a shortest vector

## 2D Reduction



If $\left|b_{1}\right|<\left|b_{2}\right|$, shrink $b_{2}$ by adding multiples of $b_{1}$

Gram-Schmidt Orthogonalization


$$
b_{2}=b_{2}^{*}+\mu b_{1}
$$

$$
b_{2}^{*} \perp b_{1}
$$

$$
\mu=\frac{\left\langle b_{2}, b_{1}\right\rangle}{\left|b_{1}\right|^{2}} \quad b_{2}^{*}, \mu \text { rational quantities }
$$

How Much to Add?

## Size Reduction

$$
\mu=-\frac{3}{2} \left\lvert\, \begin{array}{ll}
b_{2}^{\prime}=b_{2}^{*}+(\mu-\lceil\mu\rfloor) b_{1}=b_{2}^{*}+\mu^{\prime} b_{1} \\
\left|\mu^{\prime}\right| \leq \frac{1}{2}
\end{array}\right.
$$

2D Reduction
$\left|b_{2}^{\prime}\right|<\left|b_{1}\right|$, so swap and continue...


Gaussian Reduction Conditions

$$
\mu=\frac{2}{5}{\stackrel{y}{b_{2}^{\prime}}}_{b_{1}}
$$



$$
{\xrightarrow{b_{1}}}_{b_{2}} \mu=\frac{1}{2}
$$

... until no more improvement possible:

$$
\begin{gathered}
\left|b_{1}\right| \leq\left|b_{2}\right| \\
|\mu| \leq \frac{1}{2}
\end{gathered}
$$



The Gaussian Reduction Algorithm

GaussianReduce $\left(b_{1}, b_{2}\right)$ do if $\left|b_{1}\right|>\left|b_{2}\right|$ then swap $b_{1}, b_{2}$ $\mu \leftarrow \frac{\left\langle b_{2}, b_{1}\right\rangle}{\left|b_{1}\right|^{2}}$ $b_{2} \leftarrow b_{2}-\lceil\mu\rfloor b_{1}$ while $\left|b_{1}\right|>\left|b_{2}\right|$ return $\left(b_{1}, b_{2}\right)$

$$
\begin{aligned}
& \operatorname{GCD}(x, y) \\
& \text { do } \\
& \quad \text { if } x>y \text { then } \\
& \quad \text { swap } x, y \\
& \quad(x, y) \leftarrow(y \bmod x, x) \\
& \text { while } x>0 \\
& \text { return } y
\end{aligned}
$$

## Generalizing Gaussian Reduction

## Gram-Schmidt Orthogonalization in Arbitrary Dimension

$$
b_{1}^{*}=b_{1}
$$

$b_{2}^{*}$ is component of $b_{2}$ perpendicular to $b_{1}$.
$b_{3}^{*}$ is component of $b_{3}$ perpendicular to $\operatorname{span}\left(b_{1}, b_{2}\right)$. !


Gram-Schmidt Orthogonalization

$$
\begin{aligned}
b_{1}^{*} & =b_{1} \\
\mu_{i j} & =\frac{\left\langle b_{i}, b_{j}^{*}\right\rangle}{\left|b_{j}^{*}\right|^{2}} \\
b_{i}^{*} & =b_{i}-\sum_{j=1}^{i-1} \mu_{i j} b_{j}^{*}
\end{aligned}
$$



Projecting Lattices


$$
\left\{b_{1}, b_{2}, b_{3}\right\} \rightarrow\left\{b_{2}^{\prime}, b_{3}^{\prime}\right\}
$$

Project $b_{2}$ and $b_{3}$ to subspace $\perp b_{1}$

When to Swap


Apply Gaussian Reduction to $b_{2}^{\prime}, b_{3}^{\prime}$ :
Swap if $\left|b_{2}^{\prime}\right|^{2}>\frac{4}{3}\left|b_{3}^{\prime}\right|^{2}$

## The Algorithm

$$
\begin{aligned}
& \text { General }- \text { Reduction }\left(B=b_{1}, \ldots, b_{n}\right) \\
& \text { while }\left|b_{i}^{*}\right|^{2}>\frac{4}{3}\left|b_{i+1}^{*}+\mu_{i+1, i} b_{i}^{*}\right|^{2} \text { for some } i, \\
& \quad\{\text { some pair not Gaussian reduced }\} \\
& \quad \text { GaussianReduce }\left(b_{i}^{*},\left(b_{i+1}^{*}+\mu_{i+1, i} b_{i}^{*}\right)\right) \\
& \text { update } \mu_{h k} \text { and } b_{k}^{*} \text { for all } h, k . \\
& B \leftarrow \operatorname{SizeReduce}(B) \\
& \text { return } B
\end{aligned}
$$

This is the famous LLL Basis Reduction of Lenstra, Lenstra and Lovász

The Gaussian Reduction Algorithm

```
GaussianReduce( }\mp@subsup{b}{1}{},\mp@subsup{b}{2}{}
    do
        if }|\mp@subsup{b}{1}{}|>|\mp@subsup{b}{2}{}|\mathrm{ then
            swap b}\mp@subsup{b}{1}{},\mp@subsup{b}{2}{
        \mu}\frac{\langle\mp@subsup{b}{2}{},\mp@subsup{b}{1}{}\rangle}{|\mp@subsup{b}{1}{}\mp@subsup{|}{}{2}
        b}\mp@subsup{b}{2}{*}\mp@subsup{b}{2}{}-\lceil\mu\rfloor\mp@subsup{b}{1}{}\quad{\mathrm{ size-reduction }
    while }|\mp@subsup{b}{1}{}\mp@subsup{|}{}{2}>\frac{4}{3}|\mp@subsup{b}{2}{}\mp@subsup{|}{}{2
    return ( }\mp@subsup{b}{1}{},\mp@subsup{b}{2}{}
```

Size-Reduction with Gram-Schmidt

$$
\begin{aligned}
& \text { SizeReduce }\left(B=b_{1}, \ldots, b_{n}\right) \\
& \text { for } j=2, \ldots, n \\
& \quad \text { for } i=j-1, \ldots, 1 \\
& \quad b_{j} \leftarrow b_{j}-\left\lceil\mu_{j i}\right\rfloor b_{i} \\
& \mu_{j k} \leftarrow \mu_{j k}-\left\lceil\mu_{j i}\right\rfloor \mu_{i k} \text { for } k=1, \ldots, i \\
& \text { return } B
\end{aligned}
$$

$\star$ Now $\left|\mu_{i j}\right| \leq \frac{1}{2}$ for all $j<i$
$\star b_{i}^{*}$ are unchanged

## Algorithms

* $O\left(n^{4} \log S\right)$ operations on $O(n \log S)$-bit numbers, on $n \times n$ input matrix with $S$-bit coefficients.
* Improved to $O\left(n^{3} \log S\right)$ operations on $O(n+\log S)$-bit integers and floating point numbers [Schnorr, Koy '01].
* By reducing blocks rather than pairs of vectors, get $(1+\epsilon)^{n / 2}$ approximation [Schnorr '89] ( $\sim 1.5$ is practical).
* The current standard is block-reduction, sped up with pruning heuristic and floating-point Gram-Schmidt calculations, iterating several stages over the basis to be reduced. Lattices of dimension 800 and similar bit-length are practical.


## An Asymptotically Bad Basis for LLL

$$
\begin{gathered}
B=\left[\begin{array}{ccccc}
\alpha & & & & \\
\rho & \alpha \rho & & & \\
\rho^{2} & \rho^{2} & \alpha \rho^{2} & & \\
\vdots & \vdots & & \ddots & \\
\rho^{n-1} & \cdots & \cdots & \cdots & \alpha \rho^{n-1}
\end{array}\right] \\
\left|b_{i}^{*}\right|=\alpha \rho^{i-1} \\
\mu_{j i}=\frac{1}{\alpha} \rho^{j-i} \text { for } j>i \\
\left|b_{i}\right|=\rho^{i-1}(\alpha+i-1) \\
\frac{\left|b_{i+1}(i)\right|^{2}}{\left|b_{i}(i)\right|^{2}}=\frac{\alpha^{2} \rho^{2 i}+\frac{1}{4} \alpha^{2} \rho^{2 i-2}}{\alpha^{2} \rho^{2 i-2}}=\rho^{2}=\frac{1}{4} \\
(\operatorname{det} B)^{1 / n}=\alpha \rho^{(n-1) / 2}
\end{gathered}
$$

If we take $\alpha=\sqrt{3}$ and $\rho=\alpha / 2$, then $\left|b_{i+1}(i)\right|^{2} /\left|b_{i}(i)\right|^{2}=1$ and $\mu_{j i}=1 / 2$ for $j>i$, hence $B$ is LLL reduced. But the last row has length

$$
\sqrt{n \rho^{n-1} \alpha^{2}}=\sqrt{n} \rho^{(n-1) / 2} \alpha \ldots \quad \ldots \text { while }\left|b_{1}\right|=\alpha
$$

Permute this order, and it's no longer reduced. No bad basis known if rows are permuted before performing the reduction.

## Towards Schnorr's Algorithm

* LLL reduction finds shortest vectors in projected 2D blocks, and iterates

$$
\begin{array}{llllllllll}
b_{1} & b_{2} & b_{3} & \underbrace{b_{4}} \begin{array}{lllllll}
b_{5} & b_{6} & b_{7} & b_{8} & b_{9} & b_{10}
\end{array})
\end{array}
$$

* Could we improve by finding optimum of larger blocks?

$$
\begin{array}{lllllllll}
b_{1} & b_{2} & b_{3} & \underbrace{b_{4}} \begin{array}{lllllll}
b_{5} & b_{6} & b_{7} & b_{8} & b_{9} & b_{10}
\end{array}]
\end{array}
$$

* Issues:
$\diamond$ Is there an "efficient" exhaustive search to find the shortest vector?
$\diamond$ What's the right reduction to use so we can iterate?
$\diamond$ Can we prove it works?


## Korkine-Zolotareff Reduction


$\star$ For basis $B$, let $B^{\prime}=\left\{b_{2}^{\prime}, \ldots, b_{n}^{\prime}\right\}$

* $B$ is Korkine-Zolotareff reduced if

$$
\left|b_{1}\right|=\lambda(B), \text { and }
$$

$B^{\prime}$ is Korkine-Zolotareff reduced

## Why so complicated?

* A natural notion of reduction might be:

$$
\begin{gathered}
\left|b_{1}\right|=\lambda(B), \\
\left|b_{2}\right|=\lambda\left(B \backslash\left\{b_{1}\right\}\right), \text { etc. }
\end{gathered}
$$

* But such a set may not be a basis if $n \geq 5$ !

$$
\left(\begin{array}{lllll}
2 & & & & \\
& 2 & & & \\
& & 2 & & \\
& & & 2 & \\
1 & 1 & 1 & 1 & 1
\end{array}\right)
$$

* KZ reduction recurses on projected bases rather than linearly independent bases
- Easier to work with


## Block KZ Reduction: The Algorithm

* Divide basis into overlapping blocks of length $k$

$$
\overbrace{b_{1} \underbrace{b_{2} \quad b_{3} \quad b_{4}}_{\text {Block 2 }} \quad b_{5}}^{\text {Block }} b_{6} \quad b_{7} \quad b_{8}
$$

$\star$ While there exists a block that isn't KZ reduced, reduce it

* As blocks overlap, reduction of one block may provide opportunity to reduce an overlapping block
$\star$ Can prove polynomial running time (sort of...)

Block KZ Reduction: The Analysis

* Define $\alpha_{n}=\max _{k z \text { reduced }}\left|b_{1}\right|^{2} /\left|b_{n}^{*}\right|^{2}$
* Universal constant for KZ reduction
* A $k$-block KZ reduced basis satisfies

$$
\left|b_{1}\right|^{2} \leq \alpha_{k}^{n / k} \lambda(\mathcal{L})^{2}
$$

* Minkowski's Theorem implies $\alpha_{k} \leq k^{1+\ln k}$
* By setting $k$ appropriately, $k^{(1+\ln k) / k}<(1+\epsilon)$ gives the bound we want

Digression on $\alpha_{n}$

$\star\left|b_{1}\right|^{2} /\left|b_{n}^{*}\right|^{2}$ gives good metric for quality of reduction of basis
$\star$ An LLL-reduced basis has $\left|b_{1}\right|^{2} /\left|b_{n}^{*}\right|^{2} \sim 2^{n}$
$\star$ A KZ-reduced basis has $\left|b_{1}\right|^{2} /\left|b_{n}^{*}\right|^{2}=\alpha_{n} \sim n^{\ln n}$

* Quality of basis reduction much deeper than shortest vector: exponential versus quasi-polynomial


## Future Directions

* Select random subspaces of the lattice and reduce there
- Classical results (Dvortsky's Theorem) suggest lattice will behave nicely on random subspaces
* Problem: the subspace is likely to have a very short vector
* Solution: reduce across many subspaces

๑ Experimental results promising

## Random Subspace Reduction

* Select lattice subspaces $H_{1} \cdots H_{t}$ depending on basis
* Project $b_{1}$ to each subspace, rationally
* Subtract rounded sum of projected points from $b_{1}$ to get $b^{\prime}$
* Intuition:
$\diamond$ If basis not well-reduced, the $H_{i}$ will share common alignment
$\diamond$ After subtraction, $b^{\prime}$ will be more orthogonal to this alignment
* Seems to work in practice

