

A New Learning Problem with Applications To Cryptography

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Joint work with Gilbert Baumslag, Nelly Fazio, Antonio Nicolosi and Vladimir Shpilrain

- 1 Motivation & Background**
 - Why Group-Theoretic Cryptography?
 - Learning With Errors (LWE)
- 2 Generalized Learning Problems**
 - An Abstract Learning Problem
 - The Search for Instantiations: $B(n, 3)$
- 3 Symmetric-Key Cryptosystem**
 - High-Level Approach
 - Construction

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Motivation

- Interesting mathematical problem on its own . . .
- Tackling crypto challenges of post-quantum era [Sh'94]
 - Shor's algorithm: Efficient quantum procedure to compute the order of any element in a cyclic group
 - Hardness of order-finding at the heart of most popular public-key cryptosystems (RSA, Diffie-Hellman)
 - If quantum computing becomes practical, we'll need alternative cryptosystems
- Quantum computing aside, diversifying assumptions still seems prudent

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Prior Work in Non-Commutative Cryptography

Challenging computational problems abound in group theory, however...

- Many hard problems are based on infinite groups
- This makes probabilistic modeling difficult
- Average-case hardness for many problems seems to be not well-understood

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Goal

Inspired by the success of LWE and lattice-based cryptography, we seek a new source of viable intractability assumptions from learning problems in group theory.

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Let $\mathbf{s} \in \mathbb{F}_p^n$. The picture is as follows:

$$\begin{array}{ccc} \mathbb{F}_p^n & \ni & \mathbf{a} \\ \mathbf{s} \cdot _ \downarrow & & \downarrow \approx \mathbf{s} \cdot \mathbf{a} \\ \mathbb{F}_p & \ni & b = \mathbf{s} \cdot \mathbf{a} + e \end{array}$$

LWE, Informally

Roughly, the **Learning With Errors** problem is to recover \mathbf{s} by sampling preimage-image pairs in the presence of some small “noise”

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More precisely, let

- $\mathbf{s} \in \mathbb{F}_p^n$
- Ψ be a discrete gaussian distribution over \mathbb{F}_p centered at 0
- Define a distribution $\mathbf{A}_{\mathbf{s}, \Psi}$ on $\mathbb{F}_p^n \times \mathbb{F}_p$ whose samples are pairs (\mathbf{a}, b) where $\mathbf{a} \xleftarrow{\$} \mathbb{F}_p^n, b = \mathbf{s} \cdot \mathbf{a} + e, e \xleftarrow{\$} \Psi$

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 - In fact, for this case reductions from **worst-case** lattice problems have been shown ([Reg05,Pei09])
- Very recently, [AuGe11] showed a sub-exponential algorithm for noise parameters $< \sqrt{n}$

Hardness of LWE

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Learning Homomorphisms With Errors

Observation

LWE's formulation was mainly algebraic:

- Expressed in terms of homomorphisms
- Complexity reductions (worst case to average case, search to decision) also algebraic

This motivates the following

question:

Can we get learning problems with similar complexity reductions
based on non-algebraic?

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Can we learn a linear function $f(x) = ax + b$ with errors, where a and b are unknown?

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Can similar learning problems yield viable intractability assumptions based on group theory?

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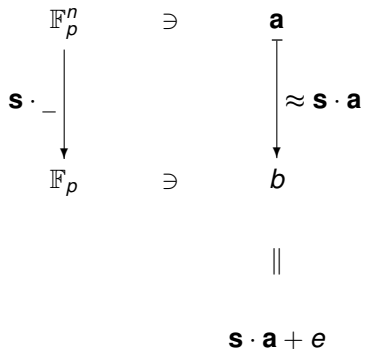
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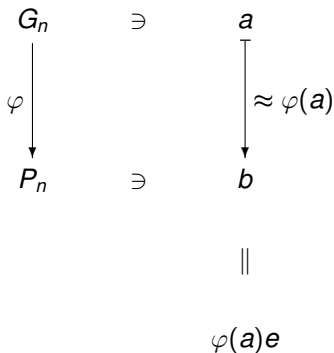
Can similar learning problems yield viable intractability assumptions based on group theory?

LWE Over Groups

Vector Spaces



Groups



Learning Homomorphisms from Images with Errors

Setup

- Let G_n and P_n be groups
- Set Γ_n, Ψ_n , distributions on G_n, P_n , resp.
- Let Φ_n be a distribution on the set of all homomorphisms, $\text{hom}(G_n, P_n)$

The Distribution A_{φ, ψ_n}

For $\varphi \stackrel{\$}{\leftarrow} \Phi_n$, define the analogous distribution A_{φ, ψ_n} on $G_n \times P_n$ whose samples are (a, b) where

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$$a \stackrel{\$}{\leftarrow} \Gamma_n;$$

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Learning Homomorphisms from Images with Errors

Search Problem

Given $\mathbf{A}_{\varphi, \psi_n}$, recover φ .

Decision Problem

Given samples from an unknown distribution
 $\mathbf{R} \in \{\mathbf{A}_{\varphi, \psi_n}, \mathbf{U}(G_n \times P_n)\}$, determine \mathbf{R} .

Hardness Assumption (Decision Version)

$$\mathbf{A}_{\varphi, \psi_n} \underset{\text{PPT}}{\approx} \mathbf{U}(G_n \times P_n)$$

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Note that this is a proper generalization of the standard LWE problem, where

- $G_n := (\mathbb{F}_p^n, +)$ and $\Gamma_n := \mathbf{U}(\mathbb{F}_p^n)$
- $P_n := (\mathbb{F}_p, +)$ and $\Psi_n :=$ discrete gaussian
- $\varphi := \mathbf{s} \cdot _$ and $\Phi_n := \mathbf{U}(\text{hom}(\mathbb{F}_p^n, \mathbb{F}_p))$

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Intuition for Hardness of LWE

Part of what makes LWE work is that \mathbb{F}_p^n is a **free module**

Free Objects

- Any mapping of generators extends to a unique homomorphism
- Homomorphisms of free objects is exponential in # generators
- Irrespective of the error distribution, with the above homomorphism possible to do image of a

So, what about free groups? Not such a good idea:

Free groups are still isomorphical to the vector space \mathbb{F}_p^n (modular)

But, \mathbb{F}_p^n is not a group

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Free groups are not commutative, so the space of possible keys is exponentially larger than the space of possible ciphertexts.

Free groups are not abelian.

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 - Subset sum is easy (no hope of a public key scheme using these techniques)
 - Length-based attacks? [MyUs07,HuTa00]

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- However, in restricted classes of groups, one can find **finite free objects**
- \mathbb{F}_p^n is actually an example, but we'll look for something more general / less constrained

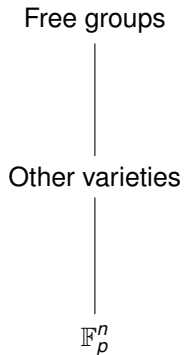
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The Search for Instantiations



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Varieties of Groups

Variety of Groups (Informal)

Roughly speaking, a **variety** is the class of all groups whose elements satisfy a certain set of equations.

Example

Abelian groups can be seen as the variety corresponding to the equation

$$XY = YX.$$

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Variety of Groups (Informal)

Roughly speaking, a **variety** is the class of all groups whose elements satisfy a certain set of equations.

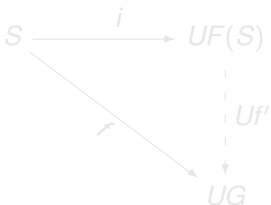
Example

Abelian groups can be seen as the variety corresponding to the equation

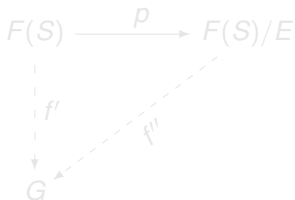
$$XY = YX.$$

Varieties of Groups

Via the usual “abstract nonsense”, it is easy to see that varieties of groups contain free objects—just take a free group and factor out the normal subgroup resulting from all the “equations”...



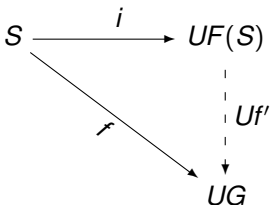
Sets



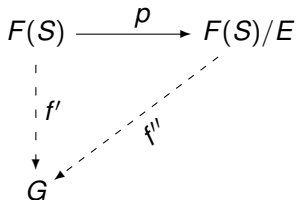
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Sets



Groups

Varieties of Groups

Question

Which varieties of groups contain **finite free objects**???

If the equations are say,

$$\begin{aligned}[X, Y] &= 1 \\ X^p &= 1\end{aligned}$$

then the free objects are exactly \mathbb{Z}_p^n , which are the objects of study in
LWE (if p is prime).

Question

What happens if the $[X, Y] = 1$ equation is removed?^a In general, the
answer is not so simple...

^aNote: $[X, Y] = X^{-1}Y^{-1}XY$.

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Notation

For the variety of groups defined by the equation $X^m = 1$, denote the free group on n generators in this variety by $B(n, m)$.

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Bounded Burnside Problem

For $n > 1$ and for sufficiently large m , it is known that $|B(n, m)| = \infty$, yet for small m , our understanding is far from complete:

$B(n, 2)$	Finite (also abelian)
$B(n, 3)$	Finite
$B(n, 4)$	Finite
$B(n, 5)$	Unknown
$B(n, 6)$	Finite
$B(n, 7)$	Unknown
\vdots	\vdots

Our Approach

We will use $B(n, 3)$ as a starting point for our investigation: it is the simplest case yielding finiteness + non-abelian.

Normal Form for $B(n, 3)$

The structure of $B(n, 3)$ is fairly well-understood. In particular we have the following

Fact

Every element of $B(n, 3)$ has a unique representation as

$$x_1^{\alpha_1} \cdots x_i^{\alpha_i} \cdots x_n^{\alpha_n} [x_1, x_2]^{\beta_{1,2}} \cdots [x_i, x_j]^{\beta_{i,j}} \cdots [x_{n-1}, x_n]^{\beta_{n-1,n}} [x_1, x_2, x_3]^{\gamma_{1,2,3}} \\ \cdots [x_i, x_j, x_k]^{\gamma_{i,j,k}} \cdots [x_{n-2}, x_{n-1}, x_n]^{\gamma_{n-2,n-1,n}}$$

where the $\{x_i\}$ are the generators, all $\alpha_i, \beta_{i,j}, \gamma_{i,j,k} \in \{0, 1, 2\}$ for all $1 \leq i < j < k \leq n$, and $[x_i, x_j, x_k] = [[x_i, x_j], x_k]$.

Corollary

Given the above normal form, we see that the order of $B(n, 3)$ is

$$3^{n + \binom{n}{2} + \binom{n}{3}}$$

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Putting the Pieces Together...

Recall the setup:

$$G_n \xrightarrow{\varphi \stackrel{s}{\leftarrow} \Phi_n} P_n$$

$$a \stackrel{s}{\leftarrow} \Gamma_n \vdash \longrightarrow \varphi(a)e, e \stackrel{s}{\leftarrow} \Psi_n$$

Instantiating the Abstract Learning Problem

- G_n
- P_n
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The error distribution requires more care...

Connection with LWE/ \mathbb{F}_3

For certain error distributions, the decision problem over $B(n, 3)$ would reduce to LWE with $p = 3$. Consider the abelianization:

$$\begin{array}{ccc} B(n, 3) & \xrightarrow{\varphi} & B(r, 3) \\ \downarrow & & \downarrow \\ \mathbb{F}_3^n & \xrightarrow{\varphi'} & \mathbb{F}_3^r \end{array}$$

$G \mapsto G/[G, G]$

This allows one to transform $\mathbf{A}_{\varphi, \psi}$ over $B(n, 3) \times B(r, 3)$ to $\mathbf{A}_{\varphi', \psi'}$ over $\mathbb{F}_3^n \times \mathbb{F}_3^r$ for some induced error distribution ψ' . Hence the $B(n, 3)$ LWE is no harder than the vector space LWE with the induced error ψ' .

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Error Distribution

In light of the preceding, we'll select an error distribution so that the abelianization construction takes $\mathbf{A}_{\varphi, \psi}$ to **the uniform distribution** $\mathbf{U}(\mathbb{F}_3^n \times \mathbb{F}_3^r)$.

Ψ_n

Let $\mathbf{v} \xleftarrow{\$} \mathbb{Z}_3^r$ and let $\sigma \xleftarrow{\$} S_r$ be a permutation. A sample from Ψ_n is an element

$$e = \prod_{i=1}^r x_{\sigma(i)}^{v_i}$$

where the $\{x_i\}$ are the generators of $B(r, 3)$ and the $\{v_i\}$ are the components of \mathbf{v} .

Moreover, notice that the normal closure of $\text{Support}(\Psi)$ is in fact the entire group $B(r, 3)$. **Intuition:** this leaves no apparent way to “factor out” the noise.

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- 2 **Generalized Learning Problems**
 - An Abstract Learning Problem
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- 3 **Symmetric-Key Cryptosystem**
 - High-Level Approach
 - Construction

High-Level Approach

- Goal: construct a simple Regev-like cryptosystem which encrypts bits
- The secret key will be a homomorphism φ
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Additional Considerations for $B(n, 3)$

For this approach to make sense, we'll need a few more ingredients:

Required Ingredients

• Norm / distance metric on $B(r, 3)$

• Large number (just by itself, not necessarily large) of samples

• ϵ

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Cayley Graph

In response to our needs for a metric, we turn to the **Cayley Graph**.

Idea

- Treat a group as a geometric object
- Vertexes are elements; edges are generators (and their inverses)
- The *norm* (denoted $\|g\|$) is just the graph distance from the identity element

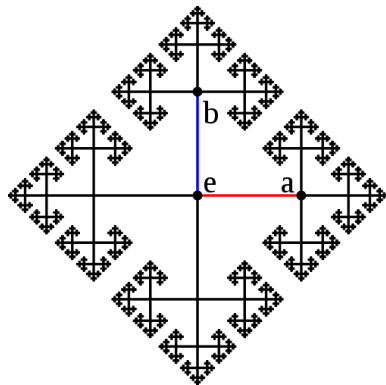


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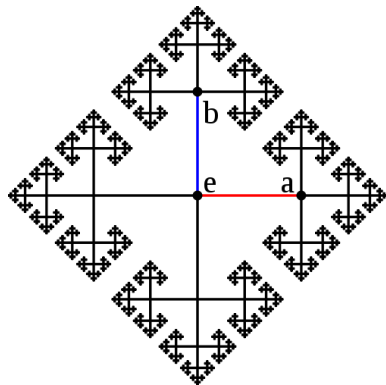


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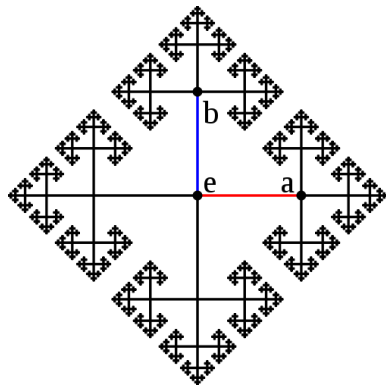


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Lemma (Diameter of $B(n, 3)$)

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Proof.

Let $d_n = \max_{x \in B(n, 3)} (\|x\|)$, and recall that $|B(n, 3)| = 3^{n + \binom{n}{2} + \binom{n}{3}}$. Since all elements of the group can be written with at most d_n symbols taken from $x_1^{\pm 1}, \dots, x_n^{\pm 1}$:

$$\begin{aligned}(2n)^{d_n} &\geq 3^{n + \binom{n}{2} + \binom{n}{3}} \\ d_n \log_3(2n) &\geq n + \binom{n}{2} + \binom{n}{3} \\ d_n &\geq \left\lceil \frac{n + \binom{n}{2} + \binom{n}{3}}{\log_3 2n} \right\rceil \quad (\text{since } d_n \in \mathbb{Z})\end{aligned}$$

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Good so far, but one issue remains: for a given $x \in G$, **how does one compute the norm** in the Cayley graph?

Computing Cayley Graph Norms

• In some cases, this is known to be NP-hard

• For example, the diameter of the Cayley graph of the symmetric group S_n with respect to the generating set of all transpositions is known to be $\lfloor 3n/2 \rfloor$. However, the diameter of the Cayley graph of S_n with respect to the generating set of all 3-cycles is unknown. It is conjectured to be $\lfloor 2n/3 \rfloor$.

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- Efficient methods may exist for $B(r, 3)$, but we can get away with small values of r , and just use breadth-first search

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Symmetric Cryptosystem

We can now proceed with a formal description of the cryptosystem.

Precomputation

Run breadth-first search on the Cayley graph of $B(r, 3)$, recording the norm of each element.

Key-Gen(n)

- 1. Run key-gen of the group G to get (g, h) .
- 2. Pick $k \in \mathbb{Z}_n$.
- 3. Shared key: $SK = g^k h$.
- 3. Sample the encryption function E using SK .

Symmetric Cryptosystem

We can now proceed with a formal description of the cryptosystem.

Precomputation

Run breadth-first search on the Cayley graph of $B(r, 3)$, recording the norm of each element.

Key-Gen(n)

- Run setup for the group LWE problem to obtain $\psi : B(n, 3) \rightarrow B(r, 3)$

Sample $x \in B(n, 3)$

Sample $y \in B(r, 3)$

Return (x, y)

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- Shared key: $SK \doteq \varphi$
- Using the precomputation, select an element $\tau \in B(r, 3)$ of maximal norm

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We can now proceed with a formal description of the cryptosystem.

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To encrypt a bit t , select $(a, b) \xleftarrow{\$} \mathbf{A}_{\varphi, \psi_n}$, compute

$$b' \doteq b\tau^t (= \varphi(a)e\tau^t)$$

and output the ciphertext $c \doteq (a, b')$.

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Compute $e' = \varphi(a)^{-1} \cdot b'$ and output $t = 0$ if and only if $\|e'\| \leq r$.

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For any group G , the norm in the Cayley metric is well-behaved with respect to the group product: for all $a, b \in G$,

$$|\|a\| - \|b\|| \leq \|ab\| \leq \|a\| + \|b\|.$$

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Theorem

Under the (decisional) LWE assumption for $B(n, 3)$, the proposed cryptosystem is IND-CPA secure.

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Given a distinguisher W that differentiates between $\mathbf{E}_0 = \text{Enc}(\text{SK}, 0)$ of encryptions of 0 from $\mathbf{E}_1 = \text{Enc}(\text{SK}, 1)$ of encryptions of 1, construct W' to distinguish $\mathbf{A}_{\varphi, \psi_n}$ from \mathbf{U} as follows. If given a distribution $\mathbf{R} \in \{\mathbf{A}_{\varphi, \psi_n}, \mathbf{U}\}$, create two distributions $\mathbf{R}_0 \doteq \mathbf{R}$ and $\mathbf{R}_1 \doteq \mathbf{R} \cdot (1, \tau)$ (i.e., \mathbf{R}_1 takes a sample (a, b) from \mathbf{R} and outputs $(a, b\tau)$).

Main point: if $\mathbf{R} = \mathbf{U}$, then $\mathbf{R}_0 = \mathbf{R}_1 = \mathbf{R}$, and if $\mathbf{R} = \mathbf{A}_{\varphi, \psi_n}$, then $\mathbf{R}_0 = \mathbf{E}_0$ and $\mathbf{R}_1 = \mathbf{E}_1$.

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Questions?

Public-Key Encryption?

The techniques of [Reg05] allow parties without any secret information to sample $\mathbf{A}_{\varphi, \psi}$ (or something close) via subset sums. Doesn't seem to apply in the non-commutative setting:

Observations

- Commutativity allows parties w/o private key to sample instances

$$\sum (a_i \cdot a_i + a_i) = \sum (a_i \cdot a_i) + \sum a_i$$

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$$\prod (\varphi(\mathbf{a}_i) e_i) \neq \prod \varphi(\mathbf{a}_i) \prod e_i$$

and hence small e_i is not sufficient for correctness.

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