

On the Soundness of Algebraic Attacks against Code-based Assumptions

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Syndrome Decoding

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Extract e out of

$$(H, s = H \cdot e)$$

where $H \in \mathbb{F}^{(n-k) \times n}$ is a **parity-check matrix** and $e \in \mathbb{F}^n$ a noise vector of **Hamming-weight** w ($\text{hw}(e) = \# \{i \in [n] \mid e_i \neq 0\}$).

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Definition (Learning Parity with Noise)

Extract x out of

$$(G, y = Gx + e)$$

where $G \in \mathbb{F}^{n \times k}$ is a **generator matrix**, $e \in \mathbb{F}^n$ of **Hamming-weight** w , and $x \in \mathbb{F}^k$.

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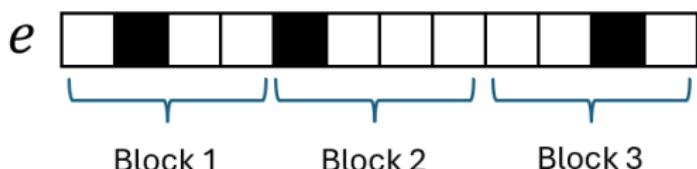
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Non-regular noise
 $(n = 12, w = 3)$



Regular noise
 $(n = 12, w = 3, b = 4)$



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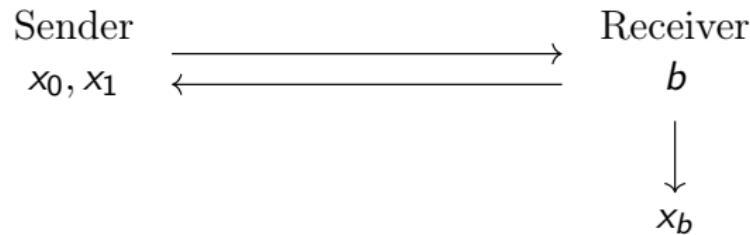
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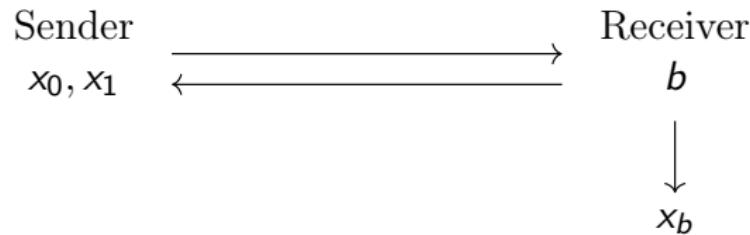
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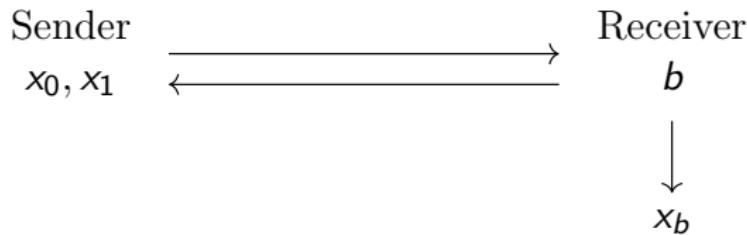
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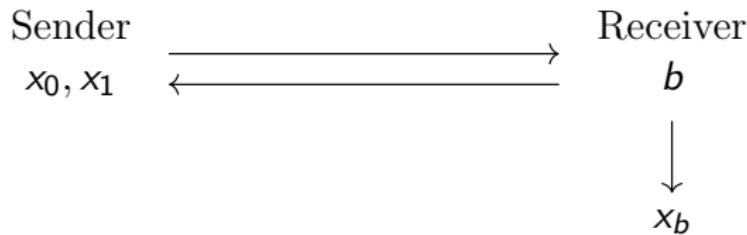


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Pseudorandom Correlation Generators (PCGs) allow for OT-extension, i.e., they stretch short strings of correlated random bits to longer strings of correlated pseudorandom bits [BCGI18, BCG⁺19, BCG⁺20].

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There are also other applications (signature schemes and local pseudorandom generators).

The Attack of Briaud and Øygarden [BØ23]

Consider $(H, s = He)$, $H \in \mathbb{F}^{(n-k) \times n}$, $e = (e^{(1)}, \dots, e^{(w)}) \in \mathbb{F}^n$,
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- ➊ Variables $E_{\alpha}^{(i)}$, $i \in [w]$, $\alpha \in [b]$, for e with equations

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Strategy: Use an XL-style algorithm to solve this equation system.

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$$M_D = \begin{pmatrix} \text{coeff}(g_1) \\ \vdots \\ \text{coeff}(g_L). \end{pmatrix}$$

Columns correspond to monomials and are sorted according to some degree-preserving monomial ordering.

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$$X_i \cdot g \notin \text{span}\{X_1^{a_1} \cdots X_k^{a_k} \cdot f_j(X)\} \text{ for some } i \in [k],$$

then add $g(X) = 0$ to the set of initial equations and go back to step 1.

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(For example, $R = \mathbb{F}[X_1, \dots, X_k]$ is graded with

$\mathbb{F}[X]^d =$ Space of homogeneous polynomials of degree d .)

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Given a series $\mathcal{H} = \sum_d c_d \cdot T^d$, its truncation is given by

$$[\mathcal{H}]_+ = \sum_{d=0}^{d_{\text{reg}}(\mathcal{H})-1} c_d \cdot T^d.$$

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Theorem ([Sal25])

The above algorithm solves^a the system $f_1(X) = \dots = f_m(X) = 0$ in time $O(k^{4D})$ where $D = d_{\text{reg}}(f_1^{\text{top}}, \dots, f_m^{\text{top}}) + 1$.

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Problem: How do we bound $d_{\text{reg}}(f_1^{\text{top}}, \dots, f_m^{\text{top}})$?

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Definition (Mathematical Semi-Regularity Over Large Fields)

A sequence of homogeneous elements $f_1, \dots, f_m \in R$ is **semi-regular** if

$$(R/(f_1, \dots, f_{i-1}))^d \longrightarrow (R/(f_1, \dots, f_{i-1}))^{d+\deg(f_i)}$$
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has full rank for all $i \in [m]$, $d \in \mathbb{N}_0$.

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Lemma

If $f_1, \dots, f_m \in R$ is semi-regular, we have

$$\mathcal{H}_{R/(f_1, \dots, f_m)}(T) = \left[(1 - T^{\deg(f_1)}) \cdots (1 - T^{\deg(f_m)}) \cdot \mathcal{H}_R(T) \right]_+.$$

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Solution: Semi-Regular Heuristic! Just assume that h_1, \dots, h_{n-k} are semi-regular.

Semi-Regularity Heuristic

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Hypothesis

A sequence of polynomials f_1, \dots, f_m from **some** distribution in **some** graded ring R will be semi-regular with **some** probability for **some** parameters.

Semi-Regularity Heuristic

Hypothesis

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Correctness of heuristic depends on various factors!

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- 2 Semiregularity Heuristic
- 3 Our Results for Regular Syndrome Decoding
- 4 Our Results for Learning With Bounded Errors

Our Results [NMSÜ25]

Let $k, n, w \in \mathbb{N}$, $n = bw$.

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Corollary

There is a PPT algorithm for the Regular Syndrome Decoding problem whenever $w \cdot \binom{b}{2} \geq 2 \binom{k+1}{2}$.

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Lemma (Schwartz-Zippel)

For $f \in \mathbb{F}[X]$, $f \neq 0$

$$\Pr_{x \leftarrow \mathbb{F}^k} [f(x) = 0] \leq \frac{\deg(f)}{\#\mathbb{F}}$$

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$$\begin{aligned}\mathcal{H}_{\mathbb{F}[E]/(h_1, \dots, h_{n-k}, E_\alpha^{(i)}, E_\beta^{(i)})}(T) &= (1 - T)^{n-k} \cdot \mathcal{H}_{\mathbb{F}[E]/(E_\alpha^{(i)}, E_\beta^{(i)})}(T) \\ &= (1 - T)^{n-k} \cdot (1 + bT + bT^2 + \dots)^w \\ &= 1 + kT + \left(\binom{k+1}{2} - w \binom{b}{2} \right) T^2 + \dots\end{aligned}$$

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According to semi-regularity hypothesis, we have

$$d_{\text{reg}} \leq 2 \iff \binom{k+1}{2} \leq w \cdot \binom{b}{2}.$$

Primal-Dual Equivalence

For $(H, s = He)$, [BØ23] considered a **dual** modeling

$$E_{\alpha}^{(i)} \cdot E_{\beta}^{(i)} = 0 \quad \text{for } i \in [w], 1 \leq \alpha < \beta \leq b,$$
$$s_j = \sum_{i \in [w], \alpha \in [b]} h_{j,\alpha}^{(i)} \cdot E_{\alpha}^{(i)} \quad \text{for } j \in [n - k].$$

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$$(y_{\alpha}^i - \sum_{j=1}^k g_{\alpha,j}^{(i)} \cdot X_j) \cdot (y_{\beta}^i - \sum_{j=1}^k g_{\beta,j}^{(i)} \cdot X_j) = 0 \quad \text{for } i \in [w], 1 \leq \alpha < \beta \leq b$$

where every row of G is given by

$$g_{\alpha}^{(i)} = (g_{\alpha,1}^{(i)}, \dots, g_{\alpha,k}^{(i)}).$$

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$$d_{\text{reg}}(\mathcal{H}_{\mathbb{F}[E]/(E_{\alpha}^{(i)} \cdot E_{\beta}^{(i)}, h_1(E), \dots, h_{n-k}(E))}) = d_{\text{reg}}(\mathcal{H}_{\mathbb{F}[X]/(g_{\alpha}^{(i)}(X) \cdot g_{\beta}^{(i)}(X))}).$$

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For the Regular LPN problem ($G, y = Gx + e$), consider the polynomial system over $\mathbb{F}[X_1, \dots, X_k]$

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Hence, the semi-regularity heuristic would imply that there are linear forms $g_1^{(1)}, \dots, g_{k-1}^{(1)}, g_1^{(2)}, \dots, g_{k-1}^{(2)} \in \mathbb{F}[X]^1$ such that

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Idea: Prove hypothesis for $w = a^2$ and $b \geq \frac{k}{a} + 1$ by constructing linear forms $(g_1^{(i)}, \dots, g_b^{(i)})_{i=1}^w \in \mathbb{F}[X]$ such that

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Prove hypothesis for $w \cdot \binom{b}{2} \geq 2\binom{k+1}{2}$ by noticing that

$$w \geq a^2 \text{ and } b \geq \frac{k}{a} + 1$$

for $a = \left\lceil \frac{k}{b-1} \right\rceil$.

Conclusion

Theorem

The semi-regularity hypothesis of [BØ23] is wrong for $w \in \{2, 3\}$. However, if $w \cdot \binom{b}{2} \geq 2 \binom{k+1}{2}$, then the dual and primal modelings of RSD have a degree of regularity of 2.

Corollary

If $w \cdot \binom{b}{2} \geq 2 \binom{k+1}{2}$, then we can solve an RSD instance (H, H_e) in time $O(n^{12})$ with probability $1 - O(k^2 / |\mathbb{F}|)$ over the randomness of $H \leftarrow \mathbb{F}^{(n-k) \times n}$.

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Learning With Bounded Errors

Let $G \in \mathbb{Z}_q^{n \times k}$ be some generator matrix.

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Extract x from

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- ① Define $f(Z) := Z \cdot (Z - 1) \cdot (Z - 2) \cdots (Z - d + 1)$.
- ② Collect degree- d equations

$$f(y_i - \sum_{j=1}^k g_{i,j} \cdot X_j) = 0.$$

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$$f(y_i - \sum_{j=1}^k g_{i,j} \cdot X_j) = 0.$$

- ③ Relinearize and solve the system once enough equations have been collected.

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Our Work [NMSÜ25]: If $q > d$ is prime, $n = \binom{k+d-1}{d}$ samples are enough.

Semiregularity by Vandermonde Matrices

Lemma

Let $\text{char } \mathbb{F} > d$ and $n = \binom{k+d-1}{d}$. When sampling $g_1, \dots, g_n \leftarrow \mathbb{F}[X]^1$, we have wop.

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$$V = \begin{pmatrix} \alpha(1)_1^{\alpha(1)_1} \cdots \alpha(1)_{k-1}^{\alpha(1)_{k-1}} & \cdots & \alpha(1)_1^{\alpha(n)_1} \cdots \alpha(1)_{k-1}^{\alpha(n)_{k-1}} \\ \vdots & \ddots & \vdots \\ \alpha(n)_1^{\alpha(1)_1} \cdots \alpha(n)_{k-1}^{\alpha(1)_{k-1}} & \cdots & \alpha(n)_1^{\alpha(n)_1} \cdots \alpha(n)_{k-1}^{\alpha(n)_{k-1}} \end{pmatrix} \in \mathbb{F}^{n \times n}.$$

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$$(g_i(X))^d = \sum_{j=1}^n \gamma_j \cdot \alpha(i)^{\alpha(j)} \cdot X_1^{\alpha(j)_1} \cdots X_{k-1}^{\alpha(j)_{k-1}} \cdot X_k^{d - \alpha(j)_1 - \cdots - \alpha(j)_{k-1}}$$

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Lemma

Let $\text{char } \mathbb{F} > d$ and $n = \binom{k+d-1}{d}$. When **sampling** $g_1, \dots, g_n \leftarrow \mathbb{F}[X]^1$, we have with probability $\geq 1 - nd / |\mathbb{F}|$

$$\text{span}_{\mathbb{F}}\{g_1(X)^d, \dots, g_n(X)^d\} = \mathbb{F}[X]^d.$$

Overview of Runtimes

		Samples	Time	Heuristical?
[AG11]	d	$O(\log(q) \cdot q \cdot k^d)$	$O(\log(q) \cdot q \cdot k^{\omega d})$	NO
[ACFP14]	2	$O(k \log \log k)$	$O\left(k^2 \cdot 2^{\frac{\omega k \log \log \log k}{8 \log \log k}}\right)$	NO
[ACFP14]	2	$c \cdot k$	$2^{O(k)}$	YES
[STA20]	2	$c \cdot k^2$	$k^{O(1/c)}$	YES
[STA20]	2	$k^{1+\alpha}$	$2^{\tilde{O}(n^{1-\alpha})}$	YES
[Ste24]	d	$> k$	$2^{O(k)}$	NO
[Ste24]	d	$O\left(\binom{k+d-1}{d}\right)$	$O\left(d^3 \cdot c_d^{(k-1)^{1-1/\ln(4)}}\right)$	YES
[Ste24]	2	$O(k^2)$	$O\left(k^2 \cdot \left(\frac{k+3}{3}\right)^{\omega+2}\right)$	YES
[NMSÜ25]	d	$\binom{k+d-1}{d}$	$O(dk^{1+d\omega})$	NO

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