

# FROM CODE-BASED CRYPTOGRAPHY TO PACKING BOUNDS

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## Code-Based Cryptography:

Building cryptographic primitives whose security relies on  
**hardness of decoding a random code**

*But how to ensure the hardness of decoding a random code?*

- ▶ Test of time,
- ▶ **Reduction:** prove that decoding is harder than another hard problem.

→ We will focus on reductions

1. Decoding Random Codes: an Average Case
2. Worst-to-Average-Case Reduction: Framework
3. Smoothing Parameter
4. Packing Bounds

# THE AVERAGE DECODING PROBLEM

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## Linear Codes: Primal Representation

A linear code  $\mathcal{C}$  is a subspace of  $\mathbb{F}_2^n$ .

Basis/Generator matrix representation: rows of  $\mathbf{A} \in \mathbb{F}_2^{k \times n}$  form a basis,

$$\mathcal{C} = \{\mathbf{sA} : \mathbf{s} \in \mathbb{F}_2^k\}$$

The vector/matrix multiplication  $\mathbf{sA}$  is the collection of inner-products

$\langle \mathbf{s}, \mathbf{a}_1 \rangle, \dots, \langle \mathbf{s}, \mathbf{a}_n \rangle$  where  $\mathbf{a}_i$  **column** of  $\mathbf{A}$  and  $\langle \mathbf{x}, \mathbf{y} \rangle \stackrel{\text{def}}{=} \sum_{i=1}^n x_i y_i \in \mathbb{F}_2$

## Hamming Weight:

$$\forall \mathbf{x} \in \mathbb{F}_2^n, \quad |\mathbf{x}| \stackrel{\text{def}}{=} \left\{ i \in \{1, \dots, n\} : x_i \neq 0 \right\}$$

- $\mathbf{e} \leftarrow \text{Ber}(p)^{\otimes n}$ : the  $e_i$ 's are **independent** and  $\mathbb{P}(e_i = x) = \begin{cases} 1-p & \text{if } x = 0 \\ p & \text{if } x \neq 0 \end{cases}$

Chernoff's Bound:  $\text{Ber}(p)^{\otimes n}$  concentrates over words of Hamming weight  $\approx np$

Given  $\mathbf{e} \leftarrow \text{Ber}(p)^{\otimes n}$ ,

$$\mathbb{E}(|\mathbf{e}|) = np \quad \text{and} \quad \mathbb{P}(|\mathbf{e}| - np| \geq \epsilon n) \leq 2 e^{-\epsilon n^2}$$

First approximation:  $\text{Ber}(p)^{\otimes n}$  is a uniform vector of Hamming weight  $np$

## A-DP( $n, k, t$ ): Average Decoding Problem

- **Input:**  $(\mathbf{A}, \mathbf{sA} + \mathbf{t})$  where  $\mathbf{A} \in \mathbb{F}_2^{k \times n}$ ,  $\mathbf{s} \in \mathbb{F}_2^k$  are uniform and  $\mathbf{t} \leftarrow \text{Ber}(t/n)^{\otimes n}$
- **Output:** recovering  $\mathbf{s}$

Algorithm  $\mathcal{A}$  solving A-DP in time  $T$  and probability  $\epsilon$  means

- $\mathcal{A}$  runs in time  $T$ ,
- Given  $\mathbf{A}, \mathbf{s}$  uniform and  $\mathbf{t} \leftarrow \text{Ber}(p)^{\otimes n}$ ,

$$\mathbb{P}_{\mathbf{A}, \mathbf{s}, \mathbf{t}} (\mathcal{A}(\mathbf{A}, \mathbf{sA} + \mathbf{t}) = \mathbf{s}) = \epsilon$$

# YOU SAID AVERAGE CASE?

- ▶ Given  $(\mathbf{A}, \mathbf{s}) \in \mathbb{F}_2^{k \times n} \times \mathbb{F}_2^k$  uniform and  $\mathbf{t} \leftarrow \text{Ber}(p)^{\otimes n}$ ,

$$\mathbb{P}_{\mathbf{A}, \mathbf{s}, \mathbf{t}} (\mathcal{A}(\mathbf{A}, \mathbf{s}\mathbf{A} + \mathbf{t}) = \mathbf{s}) = \epsilon$$

Law of total probability:

$$\epsilon = \frac{1}{2^{k \times n}} \sum_{\mathbf{s}_0, \mathbf{A}_0} \sum_t \sum_{\mathbf{t}_0: |\mathbf{t}_0|=t} \mathbb{P}(\mathcal{A}(\mathbf{A}_0, \mathbf{s}_0 + \mathbf{t}_0) = \mathbf{s}_0) \underbrace{p^t (1-p)^{n-t}}_{\mathbb{P}_t(\mathbf{t}=\mathbf{t}_0)}$$

→  $\epsilon$ : **average** success probability of  $\mathcal{A}$  over all possible inputs

$\epsilon$  small  $\implies \mathcal{A}$  fails for **almost all instances**

Assumption in Code-Based Cryptography:

A-DP is hard, *i.e.*, for any algorithm,  $T/\epsilon$  is large



To ensure hardness of decoding a random code (average hardness):

1. Test of time,
2. Reductions: solving the decoding problem on average implies an algorithm which
  - (i) computes (quantumly) short vectors in the dual code,
  - (ii) solves all instances of another decoding problem (worst-case).

# WORST-TO-AVERAGE CASE REDUCTION

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Given a fixed instance

$(G, \mathbf{xG} + \mathbf{r})$  where Hamming weight of  $\mathbf{r}$  is  $w$

we want to recover  $\mathbf{r}$

**But**, we only have an algorithm  $\mathcal{A}$  solving A-DP with probability  $\epsilon$

$$\mathbb{P}_{\mathbf{A}, \mathbf{s}, \mathbf{t}} (\mathcal{A}(\mathbf{A}, \mathbf{sA} + \mathbf{t}) = \mathbf{s}) = \epsilon$$

## Key-idea:

From  $(\mathbf{G}, \mathbf{xG} + \mathbf{r})$  build a “uniform decoding” instance being fed to  $\mathcal{A}$

1.  $\mathbf{e}_i \leftarrow \mathcal{D}$  (distribution)
2. Compute,

$$\langle \mathbf{y}, \mathbf{e}_i \rangle = \langle \mathbf{xG}, \mathbf{e}_i \rangle + \langle \mathbf{r}, \mathbf{e}_i \rangle = \underbrace{\langle \mathbf{x}, \mathbf{e}_i \mathbf{G}^\top \rangle}_{\text{secret}} + \underbrace{\langle \mathbf{r}, \mathbf{e}_i \rangle}_{\text{noise}}$$

## Packing Instances Together:

- Build the matrix  $\mathbf{A} = (\mathbf{a}_i)$  whose columns are the  $\mathbf{e}_i \mathbf{G}^\top$
- Try to decode  $(\mathbf{A}, (\langle \mathbf{y}, \mathbf{e}_i \rangle)_i) = (\mathbf{A}, \mathbf{xA} + \mathbf{t})$  where  $\mathbf{t} = (\langle \mathbf{r}, \mathbf{e}_i \rangle)_i$

From the fixed decoding instance  $\mathbf{G}, \mathbf{x}\mathbf{G} + \mathbf{r}$ , we build

$$\langle \mathbf{y}, \mathbf{e}_i \rangle = \langle \mathbf{x}\mathbf{G}, \mathbf{e}_i \rangle + \langle \mathbf{r}, \mathbf{e}_i \rangle = \underbrace{\langle \mathbf{x}, \mathbf{e}_i \mathbf{G}^\top \rangle}_{\text{secret}} + \underbrace{\langle \mathbf{r}, \mathbf{e}_i \rangle}_{\text{noise}}$$

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→ Feed  $(\mathbf{A}, (\langle \mathbf{y}, \mathbf{e}_i \rangle)_i)$  to the average decoding algorithm  $\mathcal{A}$ . **But what happens?**

- ▶ Columns of  $\mathbf{A}$ , i.e.,  $\mathbf{e}_i \mathbf{G}^\top$ , are **not** uniform
- ▶ Noise  $\langle \mathbf{r}, \mathbf{e}_i \rangle$  and  $\mathbf{e}_i \mathbf{G}^\top$  are correlated
- ▶ How does  $\langle \mathbf{r}, \mathbf{e}_i \rangle$  behave?

### Our Goal:

Estimate success probability of  $\mathcal{A}$  being fed with the biased instance  $(\mathbf{A}, (\langle \mathbf{y}, \mathbf{e}_i \rangle)_i)$

## Statistical Distance:

Given two random variables  $X, Y$ ,

$$\Delta(X, Y) = \Delta(f, g) = \frac{1}{2} \sum_a |\mathbb{P}(X = a) - \mathbb{P}(Y = a)|$$

→ It captures the differences between two random variables

- **Data processing inequality:** for any function/algorithm  $h$

$$\Delta(h(X), h(Y)) \leq \Delta(X, Y)$$

- For any event  $\mathcal{E}$ ,

$$|\mathbb{P}(X \in \mathcal{E}) - \mathbb{P}(Y \in \mathcal{E})| \leq \Delta(X, Y)$$

*If an algorithm succeeds with inputs  $X$  and probability  $\varepsilon$ , then it succeeds given  $Y$  with probability  $\varepsilon + \Delta(X, Y)$*

True average decoding instance

1. We want the following to be small:

$$\alpha \stackrel{\text{def}}{=} \Delta \left( (\mathbf{e}_i \mathbf{G}^\top, \langle \mathbf{x}, \mathbf{e}_i \mathbf{G}^\top \rangle + \langle \mathbf{r}, \mathbf{e}_i \rangle), \left( \underbrace{\mathbf{a}}_{\text{uniform}}, \langle \mathbf{x}, \mathbf{a} \rangle + \underbrace{e}_{\text{same distrib as } \langle \mathbf{r}, \mathbf{e}_i \rangle} \right) \right)$$

2. We feed  $(\mathbf{e}_i \mathbf{G}^\top, \langle \mathbf{x}, \mathbf{e}_i \mathbf{G}^\top \rangle + \langle \mathbf{r}, \mathbf{e}_i \rangle)$  to the decoding-solver  $\mathcal{A}$  with succ prob.  $\varepsilon$
3. If we give  $n$  samples to  $\mathcal{A}$ , it will recover  $\mathbf{x}$  with probability  $\varepsilon + n\alpha$

## Simplification:

Target:  $\Delta \left( \mathbf{e}_i \mathbf{G}^\top, \underbrace{\mathbf{a}}_{\text{uniform}} \right)$  small when  $\mathbf{G}$  is fixed but  $\mathbf{e}_i$  random variable.

$$\text{Aim: } \Delta \left( \mathbf{eG}^T, \underbrace{\mathbf{a}}_{\text{uniform}} \right) \text{ small}$$

Which object is  $\mathbf{eG}^T$ ?

Take the code  $\mathcal{C} \subseteq \mathbb{F}_2^n$  point of view

$$\mathcal{C} = \{ \mathbf{c} : \mathbf{cG}^T = \mathbf{0} \}$$

$\rightarrow \mathbf{eG}^T$  defines a coset of  $\mathcal{C}$

**Primal representation:**

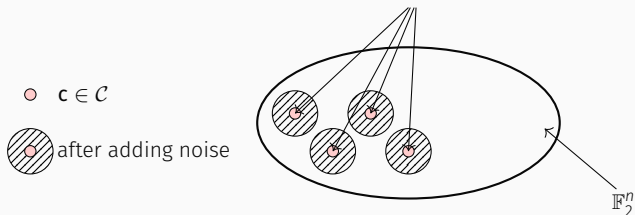
$\mathbf{eG}^T$  uniform  $\iff$  uniform in  $\mathbb{F}_2^n / \mathcal{C}$ , i.e. uniform modulo  $\mathcal{C}$

$\mathbf{eG}^T$  uniform for  $\mathbf{e} \leftarrow \mathcal{D} \iff \mathbf{c} + \mathbf{e}$  uniform in  $\mathbb{F}_2^n$  where  $\mathbf{c} \xleftarrow{\text{unif}} \mathcal{C}$  and  $\mathbf{e} \leftarrow \mathcal{D}$



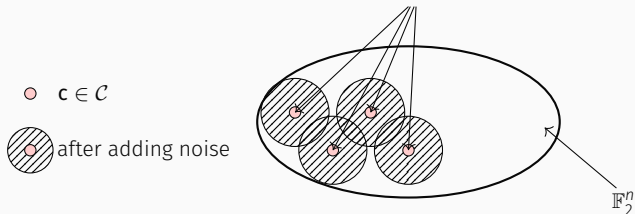
$$\mathbf{c} + \mathbf{e} \text{ uniform in } \mathbb{F}_2^n \text{ where } \mathbf{c} \xleftarrow{\text{unif}} \mathcal{C} \text{ and } \mathbf{e} \leftarrow \mathcal{D}$$

Starting from codewords and adding noise



$$\mathbf{c} + \mathbf{e} \text{ uniform in } \mathbb{F}_2^n \text{ where } \mathbf{c} \xleftarrow{\text{unif}} \mathcal{C} \text{ and } \mathbf{e} \leftarrow \mathcal{D}$$

Starting from codewords and adding noise



→ To be uniform: necessary to cover the whole space after adding noise!

$\mathbf{c} + \mathbf{e}$  uniform in  $\mathbb{F}_2^n$  where  $\mathbf{c} \xleftarrow{\text{unif}} \mathcal{C}$  and  $\mathbf{e} \leftarrow \mathcal{D}$

If  $\mathbf{e}$  concentrates over words of Hamming weight  $\leq t$ , it is necessary that

$$t \text{ is such that: } \#\mathcal{C} \cdot \binom{n}{t} \geq 2^n$$

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**Gilbert-Varshamov Radius of  $\mathcal{C}$ :**

$t_{\text{GV}}$ : smallest radius  $t_0$  such that  $\#\mathcal{C} \cdot \binom{n}{t_0} \geq 2^n$

If one targets  $\mathbf{c} + \mathbf{e}$  uniform with  $\mathbf{e}$  concentrating over words of Hamming weight  $t$ ,  
*then one wants  $t$  as small as possible which is  $t_{\text{GV}}$*

But why?

An algorithm solving the average decoding problem with noise

$$e_j = \langle \mathbf{r}, \mathbf{e}_j \rangle \quad \text{where } \mathbf{e}_j \leftarrow \mathcal{D}$$

implies an algorithm solving the fixed decoding problem  $(\mathbf{G}, \mathbf{xG} + \mathbf{r})$

The average decoding problem with noise

$$e_j = \langle \mathbf{r}, \mathbf{e}_j \rangle \quad \text{where } \mathbf{e}_j \leftarrow \mathcal{D}$$

**is harder** than solving the fixed decoding problem  $(\mathbf{G}, \mathbf{xG} + \mathbf{r})$

The average decoding problem with noise

$$e_j = \langle \mathbf{r}, \mathbf{e}_j \rangle \quad \text{where } \mathbf{e}_j \leftarrow \mathcal{D}$$

**is harder** than solving the fixed decoding problem  $(\mathbf{G}, \mathbf{xG} + \mathbf{r})$

## Ideal Situation:

The reduction works with  $\mathbb{P}(\langle \mathbf{r}, \mathbf{e}_j \rangle = 1)$  is small

Because in cryptography we use the assumption that average decoding is hard  
for a noise  $e$  with  $\mathbb{P}(e = 1)$  small

→ To ensure  $\mathbb{P}(\langle \mathbf{r}, \mathbf{e}_j \rangle = 1)$  is small we need to choose  $\mathbf{e}_j$  concentrating over words  
of small Hamming weight

# ABOUT THE NOISE DISTRIBUTION

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## Our aim:

To find  $\mathbf{e} \leftarrow \mathcal{D}$  such that  $\mathbf{c} + \mathbf{e}$  is close (stat. distance) to uniform when  $\mathbf{c} \xleftarrow{\text{unif}} \mathcal{C}$

## A first approach:

Choose each bit of  $\mathbf{e}$  with probability 1/2, then  $\mathbf{c} + \mathbf{e}$  is uniform

**But**, doing this is useless:  $\langle \mathbf{r}, \mathbf{e} \rangle$  will be a uniform noise. . .

**Therefore, impossible to solve**  $(\mathbf{e}\mathbf{G}^T, \langle \mathbf{x}, \mathbf{e}\mathbf{G}^T \rangle + \underbrace{\langle \mathbf{r}, \mathbf{e} \rangle}_{\text{noise}})$

→ We need to carefully choose  $\mathbf{e}$ !

Given a linear code  $\mathcal{C} \subseteq \mathbb{F}_2^n$ : we want

$\mathbf{c} + \mathbf{e}$  to be uniform where  $\mathbf{c} \xleftarrow{\text{unif}} \mathcal{C}$  and  $\mathbf{e} \leftarrow \mathcal{D}$  (free choice in the reduction)

$\mathcal{S}_t$  be the Hamming-sphere with radius  $t$

If  $\mathcal{D}$  concentrates over  $\mathcal{S}_t$ ,

$$\#\mathcal{C} \cdot \binom{n}{t} \geq 2^n \iff t \geq t_{\text{GV}}$$

A lower-bound on the amount of noise:

If noise concentrates on sphere with radius  $t$ : necessarily  $t \geq t_{\text{GV}}$

## Notation:

- $\text{unif}$ : uniform distribution of  $\mathbb{F}_2^n$
- $1_{\mathcal{C}}$ : indicator function of  $\mathcal{C}$
- Convolution,  $f \star g(\mathbf{x}) \stackrel{\text{def}}{=} \sum_{\mathbf{y} \in \mathbb{F}_2^n} f(\mathbf{y})g(\mathbf{x} - \mathbf{y})$

If  $\mathbf{X} \leftarrow f$  and  $\mathbf{Y} \leftarrow g$  are independent, then  $\mathbf{X} + \mathbf{Y} \leftarrow f \star g$

## Smoothing parameter:

If  $f_t$  concentrates over words of weight  $t$ . Smoothing parameter is the smallest  $t$  s.t,

$$\Delta \left( \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif} \right) = \frac{1}{2} \sum_{\mathbf{x} \in \mathbb{F}_2^n} \left| \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t(\mathbf{x}) - \text{unif}(\mathbf{x}) \right| \quad \text{is negligible}$$

## Our Dream:

$\Delta \left( \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif} \right)$  is negligible as soon as  $t = t_{\text{GV}}(1 + o(1))$ ,

We want:  $\frac{1_C}{\#C} \star f_t$  close to uniform

So,  $x \mapsto \left| \frac{1_C}{\#C} \star f_t(x) - \text{unif}(x) \right|$  **will be roughly constant!**

A Good Idea: Cauchy-Schwarz

$$\sum_{x \in \mathbb{F}_2^n} \left| \frac{1_C}{\#C} \star f_t(x) - \text{unif}(x) \right| \leq \sqrt{2^n} \sqrt{\sum_{x \in \mathbb{F}_2^n} \left( \frac{1_C}{\#C} \star f_t(x) - \text{unif}(x) \right)^2}$$

→ The upper-bound:  $L_2$ -distance!

A natural approach: Parseval's identity

- Scalar product and associated norms:

$$\langle f, g \rangle \stackrel{\text{def}}{=} \frac{1}{2^n} \sum_{\mathbf{y} \in \mathbb{F}_2^n} f(\mathbf{y})g(\mathbf{y}) \quad \text{and} \quad \|f\|_2 \stackrel{\text{def}}{=} \sqrt{\langle f, f \rangle}$$

- An orthonormal basis, characters:

$$\chi_{\mathbf{x}}(\mathbf{y}) \stackrel{\text{def}}{=} (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle}$$

Fourier Transform: given  $f : \mathbb{F}_2 \rightarrow \mathbb{C}$ ,

$$\widehat{f}(\mathbf{x}) = \frac{1}{\sqrt{2^n}} \sum_{\mathbf{y} \in \mathbb{F}_2^n} f(\mathbf{y})\chi_{\mathbf{x}}(\mathbf{y}) = \sqrt{2^n} \langle f, \chi_{\mathbf{x}} \rangle$$

- Convolution:

$$\widehat{f \star g} = \sqrt{2^n} \widehat{f} \cdot \widehat{g}$$

Parseval Identity: Fourier Transform Isometry for  $L_2$

$$\|f - g\|_2 = \|\widehat{f} - \widehat{g}\|_2$$

→ We need to compute  $\hat{1}_{\mathcal{C}}$

### Dual Code:

Given  $\mathcal{C} \subseteq \mathbb{F}_2^n$ ,

$$\mathcal{C}^\perp \stackrel{\text{def}}{=} \left\{ \mathbf{x} \in \mathbb{F}_2^n : \forall \mathbf{y} \in \mathbb{F}_2^n, \sum_i x_i y_i = 0 \right\} = \left\{ \mathbf{x} \in \mathbb{F}_2^n : \forall \mathbf{y} \in \mathcal{C} \chi_{\mathbf{x}}(\mathbf{y}) = 1 \right\}$$

### Fourier Transform of the Code Indicator:

$$\hat{1}_{\mathcal{C}} = \frac{\#\mathcal{C}}{\sqrt{2^n}} 1_{\mathcal{C}^\perp}$$

$$\begin{aligned}
\Delta\left(\frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif}\right) &\leq \sqrt{2^n} \left\| \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t - \text{unif} \right\|_2 = \sqrt{2^n} \left\| \frac{\sqrt{2^n}}{\#\mathcal{C}} \widehat{1_{\mathcal{C}}} \cdot \widehat{f_t} - \widehat{\text{unif}} \right\|_2 \\
&= \sqrt{2^n} \left\| \frac{\sqrt{2^n}}{\sqrt{2^n} \cdot \#\mathcal{C}} \cdot \#\mathcal{C} \cdot 1_{\mathcal{C}^\perp} \cdot \widehat{f_t} - \frac{1}{\sqrt{2^n}} \delta_0 \right\|_2 \\
&= \sqrt{2^n} \sqrt{\sum_{\mathbf{c}^\perp \in \mathcal{C}^\perp \setminus \{0\}} |\widehat{f_t}(\mathbf{c}^\perp)|^2}
\end{aligned}$$

Upper-Bound:

$$\Delta\left(\frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif}\right) \leq \sqrt{2^n} \sqrt{\sum_{\mathbf{c}^\perp \in \mathcal{C}^\perp \setminus \{0\}} |\widehat{f_t}(\mathbf{c}^\perp)|^2}$$

If  $f_t(\mathbf{x})$  depends only on  $|\mathbf{x}|$  (radial),

$$\Delta\left(\frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif}\right) \leq \sqrt{2^n} \sqrt{\sum_{a>0} N_a(\mathcal{C}^\perp) |\widehat{f_t}(a)|^2}$$

where,

$$N_a(\mathcal{C}^\perp) \stackrel{\text{def}}{=} \#\{\mathbf{c}^\perp \in \mathcal{C}^\perp : |\mathbf{c}^\perp| = a\}$$

## AN OPTIMAL UPPER-BOUND: THE RANDOM CASE

*We need to upper-bound  $N_a(C^\perp)$ , but how?*



# AN OPTIMAL UPPER-BOUND: THE RANDOM CASE

We need to upper-bound  $N_a(\mathcal{C}^\perp)$ , but how?

→ To understand first if our approach is meaningful, use random codes of fixed size!

$$\begin{aligned}\mathbb{E}_{\mathcal{C}^\perp} \left( \Delta \left( \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif} \right) \right) &\leq \mathbb{E}_{\mathcal{C}^\perp} \left( \sqrt{2^n} \sqrt{\sum_{a>0} N_a(\mathcal{C}^\perp) |\widehat{f}_t(a)|^2} \right) \\ &\leq \sqrt{2^n} \sqrt{\sum_{a>0} \mathbb{E}_{\mathcal{C}^\perp} \left( N_a(\mathcal{C}^\perp) |\widehat{f}_t(a)|^2 \right)} \\ &= \sqrt{2^n} \sqrt{\sum_{a>0} \frac{\binom{n}{a}}{\#\mathcal{C}} |\widehat{f}_t(a)|^2}\end{aligned}$$

**Bernoulli: our dream comes false**

Choosing  $f_t(\mathbf{x}) = p^{|\mathbf{x}|} (1-p)^{n-|\mathbf{x}|}$  concentrating over words of Hamming weight  $t = pn$  with random codes  $\mathcal{C}$  of dimension  $k$  leads to:

$$np \geq \frac{n}{2} \left( 1 - \sqrt{2^{k/n} - 1} \right)$$

To ensure  $\mathbb{E}_{\mathcal{C}^\perp} \left( \Delta \left( \frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f, \text{unif} \right) \right)$  negligible **while**

$$\frac{n}{2} \left( 1 - \sqrt{2^{k/n} - 1} \right) \gg t_{\text{GV}}$$

Using Bernoulli seems to be non-optimal. Which other distribution concentrating over  $\mathcal{S}_{pn}$  could be chosen?

Using Bernoulli seems to be non-optimal. Which other distribution concentrating over  $\mathcal{S}_{pn}$  could be chosen?

→  $1_{\mathcal{S}_t} / \binom{n}{t}$  be the uniform distribution over  $\mathcal{S}_t$

Using  $f = \frac{1_{S_t}}{\binom{n}{t}}$ ,

$$\mathbb{E}_{\mathcal{C}^\perp} \left( \Delta \left( \frac{2^n}{\#\mathcal{C}} 1_{\mathcal{C}} \star f, \text{unif} \right) \right) \leq \sqrt{\frac{2^n}{\#\mathcal{C} \cdot \binom{n}{t}}}$$

→ Our dream comes true:  $t \geq t_{\text{GV}}$  to ensure a negligible statistical distance

But our bound only holds **on average**, not for a **fixed** code  $\mathcal{C} \dots$

To get our upper-bound we used:  $\mathbb{E}_{\mathcal{C}^\perp} (\#\{\mathbf{c}^\perp \in \mathcal{C}^\perp : |\mathbf{c}^\perp| = a\}) = \frac{\binom{n}{a}}{\#\mathcal{C}}$

→ What happens for a fixed code, as aimed in the reduction?

*We will use*

**Linear Programming Bounds:**

$$N_a(\mathcal{C}^\perp) \leq F(d, a)$$

where  $d$  minimum distance of  $\mathcal{C}^\perp$

# PACKING BOUNDS

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*What we need:* to bound  $N_a(\mathcal{C})$  when the minimum distance of  $\mathcal{C}$  is fixed

### Simplification: Packing Bound

We will instead bound  $\#\mathcal{C}$  **as function of its minimum distance**

$$\max \{ \#\mathcal{C} : \mathcal{C} \subseteq \mathbb{F}_2^n \text{ and minimum distance } d \}$$

The most fruitful approach to get the best (asymptotic) packing bounds:

**theory of association schemes**

**Metric Space and Adjacency Matrix:**

$(X, \tau, n)$  be a finite metric space with  $\tau : X \times X \rightarrow \{0, \dots, n\}$ .

Its associated adjacency matrices  $\mathbf{D}_i \in \mathbb{C}^{|X| \times |X|}$  are,

$$\forall x, y \in X, \quad \mathbf{D}_i(x, y) \stackrel{\text{def}}{=} \begin{cases} 1 & \text{if } \tau(x, y) = i \\ 0 & \text{otherwise} \end{cases}$$

- ▶ Typical cases:  $X = \mathbb{F}_2^n$  **Hamming scheme** or  $X = \mathcal{S}_t$  (Hamming sphere with radius  $t$ )  
**Johnson scheme** for the Hamming distance



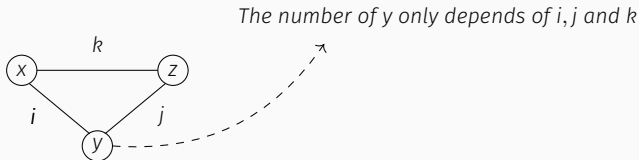
# ASSOCIATION SCHEMES: A TRIANGLE CONDITION

## Association Scheme:

$(X, \tau, n)$  is a (metric) association scheme if there exists an integer  $p_{i,j}^k$  s.t.

$$\forall x, z \in X \text{ s.t. } \tau(x, z) = k, \quad p_{i,j}^k = \#\{y \in X : \tau(x, y) = i \text{ and } \tau(y, z) = j\}$$

and  $p_{1,k}^{k+1} \neq 0$ .



## Crucial Consequences:

- ▶  $p_{i,j}^k = p_{j,i}^k$  because  $\tau$  symmetric as distance
- ▶  $\mathbf{D}_i \cdot \mathbf{D}_j = \sum_{k=0}^n p_{i,j}^k \cdot \mathbf{D}_k$

→  $\text{Vect}(\mathbf{D}_i : 0 \leq i \leq n)$  forms a **commutative** algebra  $\subseteq \mathbb{C}^{|X| \times |X|}$

$\text{Vect}(\mathbf{D}_i : 0 \leq i \leq n)$  forms a **commutative** algebra  $\subseteq \mathbb{C}^{|\mathcal{X}| \times |\mathcal{X}|}$  and the  $\mathbf{D}_i$  are symmetric

→ The  $\mathbf{D}_i$  share common orthogonal eigenspaces!

## The matrices $\mathbf{E}_j$ :

There exists **orthogonal projectors**  $\mathbf{E}_j \in \mathbb{C}^{|\mathcal{X}| \times |\mathcal{X}|}$  such that,

$$\forall i \in \{0, \dots, n\}, \quad \mathbf{D}_i = \sum_{j=0}^n p_i(j) \mathbf{E}_j$$

→ Matrices  $\mathbf{D}_i$  and  $\mathbf{E}_j$  generate the same space!

## $q$ -numbers:

$$\forall j \in \{0, \dots, n\}, \quad \mathbf{E}_j = \frac{1}{|\mathcal{X}|} \sum_{i=0}^n q_j(i) \mathbf{D}_i$$

$$D_i = \sum_{j=0}^n p_i(j)E_j \quad \text{and} \quad E_j = \frac{1}{|X|} \sum_{i=0}^n q_j(i)D_i$$

Fourier Transform and Its Inverse: given  $f : \{0, \dots, n\} \rightarrow \mathbb{C}$

$$\widehat{f}(x) \stackrel{\text{def}}{=} \sum_{y=0}^n f(y)p_y(x) \quad \text{and} \quad \widetilde{f}(x) \stackrel{\text{def}}{=} \sum_{y=0}^n f(y)q_y(x)$$

$$D^f \stackrel{\text{def}}{=} \sum_{x=0}^n f(x)D_x \quad ; \quad E^g \stackrel{\text{def}}{=} \sum_{x=0}^n g(x)E_x$$

*From the decomposition of the  $D_i$  and  $E_j$  in each basis*

$$D^f = E^{\widehat{f}} \quad \text{and} \quad E^f = D^{\widetilde{f}}$$

Our aim is to upper-bound the size of a code with minimum distance  $d$

- **Code:** given  $(X, \tau, n)$  an association scheme, a **code**  $\mathcal{C}$  is a subset of  $X$ .

$$d \stackrel{\text{def}}{=} \min (\tau(c, c') : c, c' \in \mathcal{C} \text{ and } c \neq c')$$

## Dirac/Bra-ket Notation

$X = \{x_1, \dots, x_N\}$ . For any  $x_i$ , the vector  $|x_i\rangle$  is zero except at the  $i$ th entry where it is 1.

$$|v\rangle = \begin{pmatrix} v_1 \\ \vdots \\ v_N \end{pmatrix} = \sum_{i=1}^N v_i |x_i\rangle \quad \text{and} \quad \langle v| = (\bar{v}_1 \quad \dots \quad \bar{v}_N)$$

Given a code  $\mathcal{C} \subseteq X$ ,

$$|\psi_{\mathcal{C}}\rangle \stackrel{\text{def}}{=} \frac{1}{\sqrt{\#\mathcal{C}}} \sum_{c \in \mathcal{C}} |c\rangle$$

- **Weight Distribution:**  $a(t) = \frac{1}{\#\mathcal{C}} \cdot \#((c, c') \in \mathcal{C}^2 : \tau(c, c') = t) = \langle \psi_{\mathcal{C}} | \mathbf{D}_t | \psi_{\mathcal{C}} \rangle$

$$\#\mathcal{C} = \sum_{t=0}^n a(t), \quad a(0) = 1 \quad \text{and} \quad a(t) = 0 \text{ if } t \in \{1, \dots, d-1\}$$

$$a(t) = \langle \psi_C | D_t | \psi_C \rangle \text{ where } |\psi_C\rangle \stackrel{\text{def}}{=} \frac{1}{\sqrt{C}} \sum_{c \in C} |c\rangle$$

## Dual Code Distribution:

$$a'(i) \stackrel{\text{def}}{=} \langle \psi_C | E_i | \psi_C \rangle = \langle \psi_C | \frac{1}{|X|} \sum_{t=0}^n q_i(t) D_t | \psi_C \rangle = \sum_{t=0}^n q_i(t) a'(t)$$

If  $C$  is linear, then

$$a'(i) = \#((c^\perp, d^\perp) \in C^\perp : \tau(c^\perp, d^\perp) = i)$$

Otherwise, if  $C$  is not linear maybe even not integers... But in any case:

## MacWilliams identity:

$$\forall i \in \{0, \dots, n\}, \quad a'(i) \geq 0$$

*Proof:* the  $E_i$  are projectors, i.e.,  $E_i = \sum_t |v_t^{(i)}\rangle\langle v_t^{(i)}|$  and,

$$a'(i) = \langle \psi_C | \sum_t |v_i^{(t)}\rangle\langle v_i^{(t)}| | \psi_C \rangle = \sum_t \langle \psi_C | v_i^{(t)} \rangle \langle v_i^{(t)} | \psi_C \rangle = \sum_t |\langle \psi_C | v_i^{(t)} \rangle|^2 \geq 0$$

Delsarte's Linear Program:

$$\text{DLP}(n, d) \stackrel{\text{def}}{=} \sum_{t \in \llbracket 0, n \rrbracket} u(t)$$

$$u(0) = 1$$

$$u(t) = 0 \text{ for } t \in \{1, \dots, d-1\}$$

$$u(t) \geq 0 \text{ for } t \in \{d, \dots, n\}$$

$$\sum_{t \in \llbracket 0, n \rrbracket} u(t) q_i(t) \geq 0 \text{ for } i \in \{0, \dots, n\}.$$

Given a code  $\mathcal{C}$  with minimum distance  $d$ , its weight distribution  $a(t)$  is a solution of Delsarte's linear program,

$$\#\mathcal{C} \leq A(n, d) \leq \text{DLP}(n, d)$$

→ MacWilliams identity shows that the weight distribution verifies the last condition of Delsarte's Linear Program

## Dual Delsarte Linear Program:

Let  $d \in \{0, \dots, n\}$  and  $f: \{0, \dots, n\} \rightarrow \mathbb{R}$  be a function such that,

$$\hat{f} \geq 0 \quad , \quad \hat{f}(0) > 0 \quad , \quad \forall x \geq d, f(x) \leq 0.$$

Then,

$$\max \{ \#\mathcal{C} : \mathcal{C} \subseteq \mathbb{F}_2^n \text{ and minimum distance } d \} \leq \text{DLP}(n, d) \leq |X| \cdot \frac{f(0)}{\hat{f}(0)}.$$

Obtained bounds via the choice of a function  $f$  with  $X = \mathbb{F}_2^n$ ,

- ▶ Plotkin,
- ▶ Hamming,
- ▶ Elias-Bassalygo,
- ▶ MRRW1&2 (McEliece, Rodemich, Rumsay, Welch) best bounds from '77.

- ▶ Framework for a worst-to-average-case reduction in coding theory: smoothing parameter
  - It reduces to upper-bound the weight distribution of a fixed code
- ▶ To derive upper-bounds for the weight distribution of a fixed code: use Delsarte's Linear Program approach as for packing bounds