

LECTURE 4

SELF-REDUCIBILITY OF THE DECODING PROBLEM

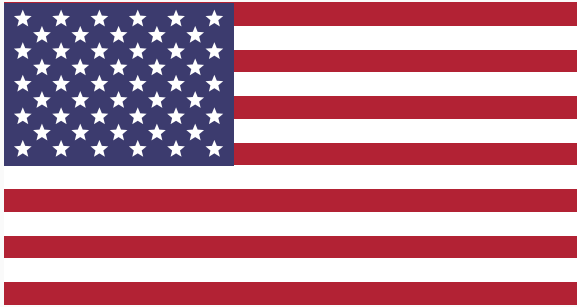
Summer School: *Introduction to Quantum-Safe Cryptography*

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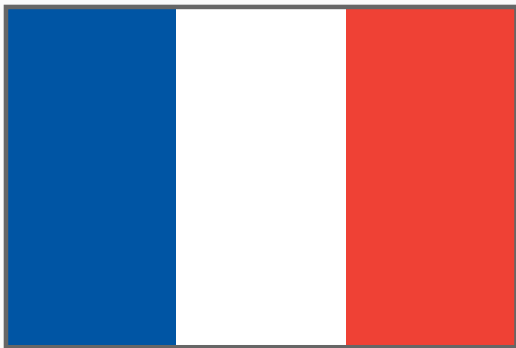
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Inria, École Polytechnique

HAPPY INDEPENDENCE DAY!



BUT DON'T FORGET...



Aim of Any **Code**-Based Cryptosystem:

Security relies on the hardness of the Decoding Problem (DP)

How to trust DP hardness?

- ▶ Test of time (designing & studying algorithms solving the decoding problem)
- ▶ **Reduction**: prove that decoding is harder than another hard problem

→ **We will focus on reductions**

- A Quick Recap: Decoding Random Codes, an Average Case
- Worst-to-Average-Case Reduction: Framework
- Smoothing Parameter
- Fourier Transform in the Hamming Cube

THE AVERAGE DECODING PROBLEM

Today: focus on **binary** codes (for the sake of simplicity)

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:

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

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

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

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

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

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

Some slight variation of the decoding problem

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 DP in time T and probability ε means

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

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

- 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:

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

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

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

Assumption in Code-Based Cryptography:

DP is hard, *i.e.*, for any algorithm, T/ϵ is large

To Ensure Hardness of DP (Average Hardness):

1. Test of time (designing & studying algorithms solving DP)
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)

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WORST-TO-AVERAGE CASE REDUCTION

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 DP with probability ϵ

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

Key-idea:

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

1. $e_i \leftarrow \mathcal{D}$ (distribution)
2. Compute,

$$\langle y, e_i \rangle = \langle xG, e_i \rangle + \langle r, e_i \rangle = \underbrace{\langle x, e_i G^T \rangle}_{\text{secret}} + \underbrace{\langle r, e_i \rangle}_{\text{noise}}$$

Packing Instances Together:

- Build the matrix $A = (a_i)$ whose columns are the $e_i G^T$
- Try to decode $(A, (\langle y, e_i \rangle)_i) = (A, xA + t)$ where $t = (\langle r, e_i \rangle)_i$

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

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

Packing Instances Together:

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

→ 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 ϵ , then it succeeds given Y with probability $\epsilon + \Delta(X, Y)$

True average decoding instance

1. We want the following to be small:

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

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

Simplification:

Target: $\Delta \left(\mathbf{e}_i \mathbf{G}^T, \underbrace{\mathbf{a}}_{\text{uniform}} \right)$ 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}

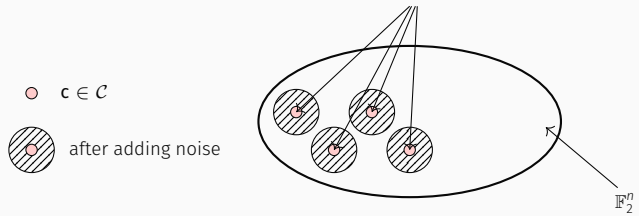
Primal Representation:

\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 $\mathbf{c} \stackrel{\text{unif}}{\leftarrow} \mathcal{C}$ and $\mathbf{e} \leftarrow \mathcal{D}$

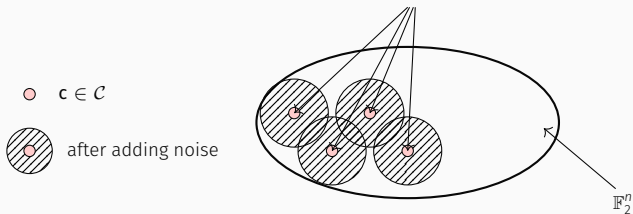
$$\mathbf{c} + \mathbf{e} \text{ uniform in } \mathbb{F}_2^n \text{ where } \mathbf{c} \xleftarrow{\text{unif}} \mathcal{C} \text{ and } \mathbf{e} \leftarrow \mathcal{D}$$

Starting from codewords and adding noise



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

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_{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_{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

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

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Ideal Situation:

The reduction works with $\mathbb{P}(\langle \mathbf{r}, \mathbf{e}_i \rangle = 1)$ 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 $\mathbb{P}(\langle \mathbf{r}, \mathbf{e}_i \rangle = 1)$ is small we need to choose \mathbf{e}_i concentrating over words
of small Hamming weight

ABOUT THE NOISE DISTRIBUTION

Our Aim:

To find $\mathbf{e} \leftarrow \mathcal{D}$ such that $\mathbf{c} + \mathbf{e}$ is close (statistical 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:

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

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

Smoothing Parameter:

If f_t concentrates over words of weight t . Smoothing parameter is the smallest t such that,

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

Our Dream:

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

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

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

Any idea to upper-bound tightly $\sum_{x \in \mathbb{F}_2^n} \left| \frac{1}{\#C} \star f_t(x) - \text{unif}(x) \right|$?

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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 **via Fourier Theory**

FOURIER TRANSFORM IN THE HAMMING CUBE

Fourier Transform (informal):

It decomposes a function in the **Fourier basis**

But how is defined the Fourier basis?

FOURIER TRANSFORM (INFORMAL)

Fourier Transform (informal):

It decomposes a function in the **Fourier basis**

But how is defined the Fourier basis?

→ Basis that diagonalizes (per-block in non-abelian case) translation operators!

Hamming Cube Case:

Given the translation operator $R(\mathbf{t})$ for functions $f : \mathbb{F}_2^n \rightarrow \mathbb{C}$,

$$R(\mathbf{t}) : f \mapsto (g : \mathbf{x} \in \mathbb{F}_2^n \mapsto g(\mathbf{x} + \mathbf{t}))$$

It is diagonal in the character basis $(\chi_{\mathbf{y}} : \mathbf{x} \mapsto (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle})$,

$$R(\mathbf{t})(\chi_{\mathbf{y}}) = (-1)^{\langle \mathbf{y}, \mathbf{t} \rangle} \cdot \chi_{\mathbf{y}}$$

- Scalar product and associated norms:

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

- An orthonormal basis, characters:

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

Fourier Transform:

Given $f: \mathbb{F}_2 \rightarrow \mathbb{C}$,

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

- Convolution:

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

Parseval Identity: Fourier Transform Isometry for L_2

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

Proof.

Given any function $h : \mathbb{F}_2^n \rightarrow \mathbb{C}$, as $(\chi_x)_{x \in \mathbb{F}_2^n}$ is an orthonormal basis,

$$h = \sum_{x \in \mathbb{F}_2^n} \langle h, \chi_x \rangle \cdot \chi_x \quad \text{and} \quad \|h\|_2^2 = \sum_{x \in \mathbb{F}_2^n} |\langle h, \chi_x \rangle|^2 = \frac{1}{2^n} \sum_{x \in \mathbb{F}_2^n} |\widehat{h}(x)|^2 = \|\widehat{h}\|_2^2$$

□

→ For our purpose: we need to compute $\widehat{1}_{\mathcal{C}}$

Dual Code:

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

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

Fourier Transform of the Code Indicator:

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

→ This result is known as “Poisson summation” formula!

FOURIER TRANSFORM UNIFORM FUNCTION

→ We also need to compute $\widehat{\text{unif}}$ where $\text{unif}(\mathbf{x}) = \frac{1}{2^n}$ for any $\mathbf{x} \in \mathbb{F}_2^n$

Fourier Transform of the Uniform Function:

$$\widehat{\text{unif}} = \frac{1}{\sqrt{2^n}} \cdot \delta_0 \quad \text{where } \delta_0(\mathbf{x}) = 0 \text{ if } \mathbf{x} \neq \mathbf{0} \text{ and } 1 \text{ otherwise (Kronecker delta)}$$

Proof.

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

But,

$$\sum_{\mathbf{y} \in \mathbb{F}_2^n} (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle} = 0 \text{ when } \mathbf{x} \neq \mathbf{0}.$$

Indeed, when $\mathbf{x} \neq \mathbf{0}$, **it exists** $\mathbf{z} \neq \mathbf{0}$ such that $\langle \mathbf{x}, \mathbf{z} \rangle \neq 0 \pmod 2$ and

$$\sum_{\mathbf{y} \in \mathbb{F}_2^n} (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle} = \sum_{\mathbf{y} \in \mathbb{F}_2^n} (-1)^{\langle \mathbf{x}, \mathbf{y} + \mathbf{z} \rangle} = (-1)^{\langle \mathbf{x}, \mathbf{z} \rangle} \sum_{\mathbf{y} \in \mathbb{F}_2^n} (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle}$$

As $(-1)^{\langle \mathbf{x}, \mathbf{z} \rangle} \neq 1$, the above equality is only possible if $\sum_{\mathbf{y} \in \mathbb{F}_2^n} (-1)^{\langle \mathbf{x}, \mathbf{y} \rangle} = 0$. □

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

Upper-Bound:

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

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,

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

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

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!

$$\begin{aligned} \mathbb{E}_{\mathcal{C}^\perp} \left(\Delta \left(\frac{1_{\mathcal{C}}}{\#\mathcal{C}} \star f_t, \text{unif} \right) \right) &\leq \mathbb{E}_{\mathcal{C}^\perp} \left(\sqrt{2^n} \sqrt{\sum_{a>0} N_a(\mathcal{C}^\perp) |\widehat{f}_t(a)|^2} \right) \\ &\leq \sqrt{2^n} \sqrt{\sum_{a>0} \mathbb{E}_{\mathcal{C}^\perp} \left(N_a(\mathcal{C}^\perp) |\widehat{f}_t(a)|^2 \right)} \quad (\text{Jensen's Inequality}) \\ &= \sqrt{2^n} \sqrt{\sum_{a>0} \frac{\binom{n}{a}}{\#\mathcal{C}} |\widehat{f}(t)|^2} \end{aligned}$$

Bernoulli: our dream comes false

Choosing $f(\mathbf{x}) = p^{|\mathbf{x}|}(1-p)^{n-|\mathbf{x}|}$ concentrating over words of Hamming weight 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 $f = \frac{1_S}{\binom{n}{t}}$,

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

→ 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: $\mathbb{E}_{\mathcal{C}^\perp} \left(\# \{ \mathbf{c}^\perp \in \mathcal{C}^\perp : |\mathbf{c}^\perp| = a \} \right) = \frac{\binom{n}{a}}{\#\mathcal{C}}$

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

We use

Linear Programming Bounds from Delsarte's Theory (Association Schemes, ...):

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

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

