

# LECTURE 8

## RANDOM LINEAR CODES AND SHANNON'S THEOREM

Information Theory

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## Lecture 6:

*It is possible to communicate  $Rn$  bits by sending  $n$  bits through a noisy channel  $Q$  if and only if*

$$R \leq C(Q) \text{ (capacity)}$$

→ The proof relies on the use of **block-codes**:

we encode a symbol into a block-code which adds **redundancy**

### Issue:

Shannon's proof does not give an **efficient algorithm** to communicate: even encoding is non-efficient with block-codes

*Lecture 7:*

*We introduced **linear** codes which enable at least an efficient encoding*

**Issue:**

Linear codes form a **sub-class** of block-codes: we don't know if they reach the capacity of noisy channels

Linear codes reach the capacity of the  $q$ -ary Symmetric Channel ( $qSC(p)$ ), but. . .

- ▶ The proof which is a variation of Shannon's proof from Lecture 6 does not exhibit an efficient decoding algorithm (a priori the decoding algorithm requires computations with an exponential cost)

1. Shannon's Theorem for Linear Codes
2. About Random Codes
3. Proof of Shannon's Theorem for Linear Codes
4. Random Codes: a Powerful Tool
5. A Little Bit of Cryptography

# SHANNON'S THEOREM

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$q$ -ary symmetric ( $q$ SC( $p$ )) channels:

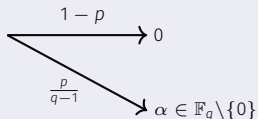
Memoryless channel  $(\mathbb{F}_q, \mathbb{F}_q, p(y | x))$  where,

$$\forall x, y \in \mathbb{F}_q, p(y | x) = \begin{cases} 1 - p & \text{if } x = y \\ \frac{p}{q-1} & \text{otherwise} \end{cases}$$

$p$ : probability of error ;  $\frac{p}{q-1}$  transition probability

When sending  $\mathbf{c} \in \mathbb{F}_q^n$  through the channel

$$\mathbf{y} = \mathbf{c} + \mathbf{e} \text{ where the } e_i \text{ are i.i.d and } p(e_i = x) = \begin{cases} 1 - p & \text{if } x = 0 \\ \frac{p}{q-1} & \text{otherwise} \end{cases}$$



**Decoder:**

A **decoder**  $\mathcal{D}$  is defined as a mapping  $\mathcal{D} : \mathbb{F}_q^n \mapsto \mathbb{F}_q^n \cup \{\perp\}$  where  $\perp$  is a special symbol used to denote the potential case where the decoder fails to output something

Given a code  $\mathcal{C}$ , we can associate a decoder  $\mathcal{D}$  to form the pair  $(\mathcal{C}, \mathcal{D})$ . The **failure probability** of  $\mathcal{D}$  relatively to  $\mathcal{C}$  is defined as

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}) \stackrel{\text{def}}{=} \mathbb{P}(\mathcal{D}(\mathbf{c} + \mathbf{e}) \neq \mathbf{c})$$

where the probability is computed over: (i) the internal randomness of  $\mathcal{D}$ , (ii)  $\mathbf{c}$  be chosen uniformly at random among  $\mathcal{C}$  **and** (iii)  $\mathbf{e}$  be the error induced by the  $q\text{SC}(p)$ , i.e.,

$$\mathbf{e} = (e_1, \dots, e_n) \text{ where the } e_i \text{ are i.i.d and } p(e_i = x) = \begin{cases} 1 - p & \text{if } x = 0 \\ \frac{p}{q-1} & \text{otherwise} \end{cases}$$



## Maximum likelihood decoder:

Given the  $q$ SC( $p$ ) and  $\mathcal{C} \subseteq \mathbb{F}_q^n$ , we call the maximum likelihood decoder the map

$$\mathcal{D}_{\text{ML}} : \mathbb{F}_q^n \longrightarrow \mathcal{C}$$

such that given  $\mathbf{y} \in \mathbb{F}_q^n$ , it outputs the codeword  $\mathbf{c} \in \mathcal{C}$  maximizing the transition probabilities

$$\mathcal{D}_{\text{ML}}(\mathbf{y}) \stackrel{\text{def}}{=} \arg \max_{\mathbf{c} \in \mathcal{C}} \mathbb{P}(\mathbf{c} | \mathbf{y}) = \arg \max_{\mathbf{c} \in \mathcal{C}} \prod_{i=1}^n \mathbb{P}(c_i | y_i)$$

## Proposition (from Lecture 7):

In a  $q$ SC( $p$ ) with probability of transition  $p/(q-1) < 1/q$ , if codewords  $\mathbf{c} \in \mathcal{C}$  are chosen uniformly at random among  $\mathcal{C}$ , then

$$\forall \mathbf{y} \in \mathbb{F}_q^n, \quad \mathcal{D}_{\text{ML}}(\mathbf{y}) = \mathbf{c} \in \mathcal{C} \quad \text{such that } \mathbf{c} = \arg \min_{\mathbf{d} \in \mathcal{C}} d_{\text{H}}(\mathbf{y}, \mathbf{d})$$

where  $d_{\text{H}}(\cdot, \cdot)$  is **the Hamming distance**,

$$\forall \mathbf{x}, \mathbf{y} \in \mathbb{F}_q^n, \quad d_{\text{H}}(\mathbf{x}, \mathbf{y}) \stackrel{\text{def}}{=} \#\{i \in [1, n], x_i \neq y_i\}$$

Remember, an  $[n, k]_q$ -code is a subspace of  $\mathbb{F}_q^n$  with dimension  $k$

### Asymptotic sequence of codes:

A sequence of codes  $(\mathcal{C}_n)_{n \in \mathbb{N}}$  is defined as a series of  $[n, k]_q$ -codes where  $k$  is a function of  $n$ , i.e.,

$$k : n \in \mathbb{N} \mapsto k(n) \in \llbracket 0, n \rrbracket$$

→ Be careful, abuse of notation: we write  $k$  instead of  $k(n)$

### Rate of asymptotic sequence of codes:

Given a sequence of codes  $(\mathcal{C}_n)_{n \in \mathbb{N}}$ , its rate is defined as (if the following limit exists),

$$R \stackrel{\text{def}}{=} \lim_{n \rightarrow +\infty} \frac{k}{n} \quad \left( = \lim_{n \rightarrow +\infty} \frac{k(n)}{n} \right)$$

## $q$ -ary entropy

The  $q$ -ary entropy is defined as,

$$h_q : x \in [0, 1] \mapsto -x \log_q \frac{x}{q-1} - (1-x) \log_q (1-x)$$

## Exercise:

Let  $X \in \llbracket 0, q-1 \rrbracket$  where,

$$\mathbb{P}(X = x) = \begin{cases} 1-p & \text{if } x = 0 \\ \frac{p}{q-1} & \text{if } x \neq 0 \end{cases}$$

Show that the  $q$ -ary entropy is the entropy of  $X$  up to  $\log_2 q$  factor, i.e.,

$$h_q(p) = \frac{1}{\log_2 q} \cdot H(X)$$

## Shannon's Theorem for Linear Codes:

For all  $0 \leq p < \frac{q-1}{q}$  and  $\varepsilon > 0$  it holds that,

1. It exists  $\delta > 0$  such that for **any**  $n$  large enough it exists  $(\mathcal{C}, \mathcal{D})$  where  $\mathcal{C}$  is a linear code of length  $n$  and dimension  $n(1 - h_q(p) - \varepsilon)$  and

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}) \leq \frac{1}{q^{\delta n}}$$

2. For all  $\delta > 0$  and  $n$  large enough, and all pair  $(\mathcal{C}, \mathcal{D})$ , where  $\mathcal{C}$  is a linear code with length  $n$  and dimension  $n(1 - h_q(p) + \varepsilon)$ , we have

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}) \geq 1 - \delta$$

→ In particular: the proof of Shannon's theorem for linear codes uses the maximum likelihood decoder, **not** the jointly typical decoder!

## An important remark:

Linear codes enable to achieve reliable communication over  $q\text{SC}(p)$  but under the necessary and sufficient condition to have a transmission rate

$$R = k/n < 1 - h_q(p)$$

But  $(1 - h_q(p))$  is exactly the capacity, as defined in Lecture 6, of the  $q\text{SC}(p)$  channel

1. As with block codes we will use the average code trick but by picking them as uniform  $[n, k]_q$ -codes (not a coincidence, capacity of  $qSC(p) = \max_{\mathbf{X}} I(\mathbf{X}, \mathbf{Y})$  achieved for a uniform  $\mathbf{X}$ )
2. Our decoder choice will be the maximum likelihood decoder
3. We will show that errors of the  $qSC(p)$  concentrate over Hamming ball of radius  $np$
4. Then for "random codes" balls centered at codewords and with radius  $np$  do not typically intersect at the condition

$$\#\mathcal{C} \cdot \text{Vol}(\mathcal{B}(np)) = q^k \cdot \text{Vol}(\mathcal{B}(np)) \leq \#\mathbb{F}_q^n = q^n \iff k < n(1 - h_q(p))$$

5. As above balls do not intersect under the good condition, the maximum likelihood decoder works because it outputs the closest codeword (for the Hamming distance)

*The average trick is the crucial idea of the proof*

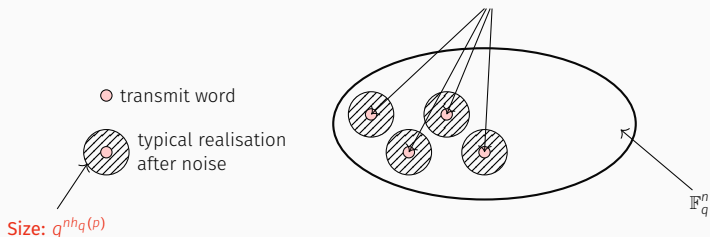
→ If a quantity is  $< \epsilon$  in average over  $\{A\}$ , then it exists an  $A_0$  s.t the quantity is  $< \epsilon$  for this  $A_0$

## SOME PICTURE: AVOID CONFUSION

Errors  $\mathbf{e}$  in the  $q$ SC( $p$ ) are such that  $|\mathbf{e}| \approx np$

→ There are  $\approx q^{nh_q(p)}$  vectors of Hamming weight  $\approx np$

$q^{n(1-h_q(p))}$  words can be transmitted without confusion



In Shannon's theorem we use the maximum likelihood-decoder: from  $\mathbf{y} \in \mathbb{F}_q^n$  it outputs  $\mathbf{c} \in \mathcal{C}$ , **the closest codeword for the Hamming distance!**

As soon as the code size is  $> q^{n(1-h_q(p))}$  an exponential number of balls intersect:  
it is impossible to recover the sent codeword without ambiguity

## ABOUT RANDOM CODES

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**Random code(s):**

It is defined as

- $\mathcal{C} = \{ \mathbf{m} \mathbf{G}_U : \mathbf{m} \in \mathbb{F}_q^k \}$  where  $\mathbf{G}_U \leftarrow \text{Unif}(\mathbb{F}_q^{k \times n})$

or,

- $\mathcal{C} = \{ \mathbf{c} \in \mathbb{F}_q^n : \mathbf{H}_U \mathbf{c}^T = \mathbf{0} \}$  where  $\mathbf{H}_U \leftarrow \text{Unif}(\mathbb{F}_q^{(n-k) \times n})$

where  $\text{Unif}(\mathbb{F}_q^{m \times n})$  means the uniform distribution over  $\mathbb{F}_q^{m \times n}$ , i.e., coefficients the matrix are i.i.d. and uniform over  $\mathbb{F}_q$

**Exercise:**

Are these models equivalent? Do they define a uniform  $[n, k]_q$ -code?



## Random code(s):

- $\mathcal{C} = \{m\mathbf{G}_u : m \in \mathbb{F}_q^k\}$  where  $\mathbf{G}_u \leftarrow \text{Unif}(\mathbb{F}_q^{k \times n})$   
 $\rightarrow \dim \mathcal{C} \leq k$  as  $\text{rank}(\mathbf{G}_u) \leq k$
- $\mathcal{C} = \{c \in \mathbb{F}_q^n : \mathbf{H}_u c^T = \mathbf{0}\}$  where  $\mathbf{H}_u \leftarrow \text{Unif}(\mathbb{F}_q^{(n-k) \times n})$   
 $\rightarrow \dim \mathcal{C} \geq k$  as  $\text{rank}(\mathbf{H}_u) \leq n - k$

Both models **do not seem to be equivalent**. . . (Spoiler: they “are”!)

and they don’t define uniform  $[n, k]_q$ -codes. . .

**Random code(s):**

It is defined as

- $\mathcal{C} = \{m\mathbf{G}_k : m \in \mathbb{F}_q^k\}$  where  $\mathbf{G}_k \leftarrow \text{Unif} \{ \mathbf{M} \in \mathbb{F}_q^{k \times n} \text{ with rank } k \}$

or,

- $\mathcal{C} = \{c \in \mathbb{F}_q^n : \mathbf{H}_k c^T = \mathbf{0}\}$  where  $\mathbf{H}_k \leftarrow \text{Unif} \{ \mathbf{M} \in \mathbb{F}_q^{(n-k) \times n} \text{ with rank } n - k \}$

→ Both models are equivalent: they pick a code uniformly at random among  $[n, k]_q$ -codes

**Issue:**

These models imply in many situations unnecessarily complex computations contrary to the cases where we don't fix the rank of the matrix. . .

*But could it be that all these models are “equivalent”?*

## Statistical distance:

Let  $X$  and  $Y$  be random variables,

$$\Delta(X, Y) \stackrel{\text{def}}{=} \frac{1}{2} \sum_{a \in \mathcal{E}} \left| \mathbb{P}(X = a) - \mathbb{P}(Y = a) \right|$$

## A crucial property: data processing inequality

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

**Consequence:**  $\forall \mathcal{A}$  algorithm

$$\left| \mathbb{P}_X(\mathcal{A}(X) = \text{“success”}) - \mathbb{P}_Y(\mathcal{A}(Y) = \text{“success”}) \right| \leq \Delta(X, Y)$$

## Typical situation:

We want to analyse the success probability of  $\mathcal{A}(\mathbf{m})$  when its input  $\mathbf{m}$  is picked according to  $X$ . But it implies ugly computations. . . However, we know how to analyse this success probability when  $\mathbf{m}$  picked according to  $Y$ . If  $\Delta(X, Y)$  is small we are done! We perform computations with  $Y$ , what we loose in our estimation of the success probability is  $\pm \Delta(X, Y)$

$G_U$  or  $H_U$ -models  $\iff$  draw uniformly an  $[n, k]$ -code:

$G_k \in \mathbb{F}_q^{k \times n}$  ( $H_k \in \mathbb{F}_q^{(n-k) \times n}$ ) be uniform of rank  $k$  (resp.  $n - k$ ):

$$\Delta(G_U, G_k) = O(q^{-(n-k)}) \quad (\text{resp. } \Delta(H_U, H_k) = O(q^{-k}))$$

Computation are the same in  $G_U$  and  $H_U$ -models:

Let  $\mathcal{E}$  be a set of codes (defined as an event). We have,

1.

$$|\mathbb{P}_{G_k}(\mathcal{E}) - \mathbb{P}_{H_k}(\mathcal{E})| = 0$$

2.

$$|\mathbb{P}_{G_U}(\mathcal{E}) - \mathbb{P}_{H_U}(\mathcal{E})| = O(q^{-\min(k, n-k)})$$

Proof:

$$\left| \mathbb{P}_{\mathbf{G}_U}(\mathcal{E}) - \mathbb{P}_{\mathbf{H}_U}(\mathcal{E}) \right| \leq \left| \mathbb{P}_{\mathbf{G}_U}(\mathcal{E}) - \mathbb{P}_{\mathbf{G}_R}(\mathcal{E}) \right| + \left| \mathbb{P}_{\mathbf{H}_R}(\mathcal{E}) - \mathbb{P}_{\mathbf{H}_U}(\mathcal{E}) \right| + \left| \mathbb{P}_{\mathbf{G}_R}(\mathcal{E}) - \mathbb{P}_{\mathbf{H}_R}(\mathcal{E}) \right|$$

- $\left| \mathbb{P}_{\mathbf{G}_U}(\mathcal{E}) - \mathbb{P}_{\mathbf{H}_U}(\mathcal{E}) \right|$  and  $\left| \mathbb{P}_{\mathbf{H}_R}(\mathcal{E}) - \mathbb{P}_{\mathbf{H}_U}(\mathcal{E}) \right|$  are  $O(q^{-\min(k, n-k)})$  because of the statistical distance
- $\mathbb{P}_{\mathbf{G}_R}(\mathcal{E}) = \mathbb{P}_{\mathbf{H}_R}(\mathcal{E})$  because codes defined by  $\mathbf{G}_R$  and  $\mathbf{H}_R$  have the same distribution: uniform over  $[n, k]_q$ -codes

# SHANNON'S THEOREM: PROOF

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**Hamming ball:**

The Hamming ball of center  $\mathbf{x}$  and radius  $r \in \llbracket 0, n \rrbracket$  is defined as,

$$\mathcal{B}_H(\mathbf{x}, r) = \left\{ \mathbf{y} \in \mathbb{F}_q^n, d_H(\mathbf{x}, \mathbf{y}) \leq r \right\}$$

→ The volume of  $\mathcal{B}_H(\mathbf{x}, r)$  is given by  $\sum_{j=0}^r \binom{n}{j} (q-1)^j$ , it is independent from  $\mathbf{x}$

**Lemma (see Exercise Session 5):**

for all  $0 \leq r \leq \frac{q-1}{q}n$ ,

$$\frac{1}{n+1} q^{nh_q(r/n)} \leq \binom{n}{r} (q-1)^r \leq q^{nh_q(r/n)}, \text{ then } \#\mathcal{B}_H(\mathbf{x}, r) = q^{n(h_q(r/n)+o(1))}$$

*Intuitive proof:* a  $q$ -ary Bernoulli with parameter concentrates exactly over the shell of  $\mathcal{B}_H(\mathbf{0}, r)$

(Chernoff bound) but we know that the number of typical sequence of this distribution is

$q^{nh_q(r/n)}$ . To conclude, the volume of a ball is  $\approx$  given by its shell (or  $x \mapsto h_q(x)$  is increasing over

$$[0, (q-1)/q])$$

From Lecture 7:

**Proposition:**

In a  $q$ SC( $p$ ) with probability of transition  $p/(q-1) < 1/q$ , if codewords  $\mathbf{c} \in \mathcal{C}$  are chosen uniformly at random among  $\mathcal{C}$ , then

$$\forall \mathbf{y} \in \mathbb{F}_q^n, \mathcal{D}_{\text{ML}}(\mathbf{y}) = \arg \max_{\mathbf{c}_0 \in \mathcal{C}} \mathbb{P}(\mathbf{c}_0 | \mathbf{y}) = \mathbf{c} \in \mathcal{C} \text{ such that } \mathbf{c} = \arg \min_{\mathbf{d} \in \mathcal{C}} d_{\text{H}}(\mathbf{y}, \mathbf{d})$$

where  $d_{\text{H}}(\cdot, \cdot)$  is **the Hamming distance**,

$$\forall \mathbf{x}, \mathbf{y} \in \mathbb{F}_q^n, d_{\text{H}}(\mathbf{x}, \mathbf{y}) \stackrel{\text{def}}{=} \#\{i \in [1, n], x_i \neq y_i\}$$

**Lemma: maximum likelihood decoder and the linearity**

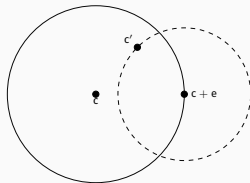
Let  $\mathcal{C} \subseteq \mathbb{F}_q^n$  be a **linear** code, and  $\mathbf{e}$  be the error induced by  $q$ SC( $p$ ),

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) = \mathbb{P}(\mathcal{D}_{\text{ML}}(\mathbf{c} + \mathbf{e}) \neq \mathbf{c}) = \mathbb{P}_{\mathbf{e}}(\mathcal{D}_{\text{ML}}(\mathbf{e}) \neq \mathbf{0})$$

or equivalently,

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) = \mathbb{P}_{\mathbf{e}}\left(\exists \mathbf{c} \in \mathcal{B}_{\text{H}}(\mathbf{e}, |\mathbf{e}|) \cap \mathcal{C} \setminus \{\mathbf{0}\}\right)$$



**Proof:**

Given  $\mathbf{c} \in \mathcal{C}$  be chosen uniformly at random and  $\mathbf{e}$  be the error induced by  $q\text{SC}(p)$ . The maximum likelihood decoder  $\mathcal{D}_{\text{ML}}$  will fail given  $\mathbf{y} \stackrel{\text{def}}{=} \mathbf{c} + \mathbf{e}$  if there is another codeword  $\mathbf{c}' \in \mathcal{C}$  such that  $|\mathbf{y} - \mathbf{c}'| \leq |\mathbf{y} - \mathbf{c}|$

$$\begin{aligned} \mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) &= \mathbb{P}(\exists \mathbf{c}' \in \mathcal{B}_{\text{H}}(\mathbf{c} + \mathbf{e}, |\mathbf{e}|) \cap \mathcal{C} \setminus \{\mathbf{c}\}) \\ &= \frac{1}{q^k} \sum_{\mathbf{c}_0 \in \mathcal{C}} \mathbb{P}(\exists \mathbf{c}' \in \mathcal{B}_{\text{H}}(\mathbf{c}_0 + \mathbf{e}, |\mathbf{e}|) \cap \mathcal{C} \setminus \{\mathbf{c}_0\}) \quad (\text{law of total probability}) \\ &= \frac{1}{q^k} \sum_{\mathbf{c}_0 \in \mathcal{C}} \mathbb{P}(\exists \mathbf{c}' \in \mathcal{B}_{\text{H}}(\mathbf{e}, |\mathbf{e}|) \cap \mathcal{C} \setminus \{\mathbf{0}\}) \end{aligned}$$

where in the last equality we used that fact that  $\mathcal{C}$  is linear by applying a translation  $-\mathbf{c}_0$ . Then,

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) = \mathbb{P}_{\mathbf{e}}(\exists \mathbf{u} \in \mathcal{B}_{\text{H}}(\mathbf{e}, |\mathbf{e}|) \cap \mathcal{C} \setminus \{\mathbf{0}\}) = \mathbb{P}_{\mathbf{e}}(\mathcal{D}_{\text{ML}}(\mathbf{e}) \neq \mathbf{0})$$

In the proof of Shannon's theorem will use as model of random codes:

$\mathbf{G}_k$  be a uniform matrix over  $\mathbb{F}_q^{k \times n}$  with rank  $k$

#### Lemma:

For all (fixed)  $\mathbf{m} \in \mathbb{F}_q^k \setminus \{\mathbf{0}\}$ , the random variable  $\mathbf{m}\mathbf{G}_k$  is uniform over  $\mathbb{F}_q^n \setminus \{\mathbf{0}\}$

#### Proof:

Let  $\mathbf{y}, \mathbf{y}' \in \mathbb{F}_q^n \setminus \{\mathbf{0}\}$ : we will prove that  $\mathbb{P}(\mathbf{m}\mathbf{G}_k = \mathbf{y}) = \Pr(\mathbf{m}\mathbf{G}_k = \mathbf{y}')$

First, it exists an invertible  $n \times n$  matrix  $\mathbf{M}$  such that  $\mathbf{y}\mathbf{M} = \mathbf{y}'$ . Therefore,

$$\mathbb{P}(\mathbf{x}\mathbf{G}_k = \mathbf{y}) = \mathbb{P}(\mathbf{x}\mathbf{G}_k\mathbf{M} = \mathbf{y}')$$

Since  $\mathbf{A} \mapsto \mathbf{A}\mathbf{M}$  is a bijection from the set of full rank  $k \times n$  matrices onto itself,  $\mathbf{G}_k\mathbf{M}$  is a uniformly random full rank  $k \times n$  matrix and,

$$\mathbb{P}(\mathbf{x}\mathbf{G}_k\mathbf{M} = \mathbf{y}') = \mathbb{P}(\mathbf{x}\mathbf{G}_k = \mathbf{y}')$$

Combining the previous equality concludes the proof

## Proof of Shannon's theorem:

Let  $k = \lfloor (1 - h_q(p) - \varepsilon)n \rfloor$ . Let  $\mathcal{C}$  be an  $[n, k]_q$ -code and  $\mathbf{G}$  be a generator matrix for  $\mathcal{C}$ . We have proved,

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) = \mathbb{P}_{\mathbf{e} \leftarrow q\text{SC}(p)} \left( \exists \mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}, \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{e}, |\mathbf{e}|) \right)$$

Let  $\mathcal{E}(\mathbf{G}, \mathbf{e})$  be the event:  $\mathcal{E}(\mathbf{G}, \mathbf{e}) \stackrel{\text{def}}{=} \left\{ \exists \mathbf{m} \in (\mathbb{F}_q^k \setminus \{0\}), \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{e}, |\mathbf{e}|) \right\}$ . Let  $\gamma > 0$ , then,

$$\begin{aligned} \mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) &= \mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}, \mathbf{e}) \mid |\mathbf{e}| \leq (p + \gamma)n \right) \mathbb{P}_{\mathbf{e}} \left( |\mathbf{e}| \leq (p + \gamma)n \right) \\ &\quad + \mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}, \mathbf{e}) \mid |\mathbf{e}| > (p + \gamma)n \right) \mathbb{P}_{\mathbf{e}} \left( |\mathbf{e}| > (p + \gamma)n \right) \end{aligned}$$

Since probabilities are always less than or equal to 1, we get

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) \leq \mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}, \mathbf{e}) \mid |\mathbf{e}| \leq (p + \gamma)n \right) + \mathbb{P}_{\mathbf{e}} \left( |\mathbf{e}| > (p + \gamma)n \right)$$

Thanks to Chernoff bound,

$$\mathbb{P}_{\mathbf{e}} \left( |\mathbf{e}| > (p + \gamma)n \right) \leq 2e^{-2pn\gamma^2}$$

## Conclusion:

To conclude it remains to upper-bound:  $\mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}, \mathbf{e}) \mid |\mathbf{e}| \leq (p + \gamma)n \right)$

→ Use the average trick over  $\mathbf{G}$

## PROOF OF SHANNON'S THEOREM(II)

It remains to get an upper bound on  $\mathbb{P}_e(\mathcal{E}(\mathbf{G}, \mathbf{e}) \mid |\mathbf{e}| \leq (\rho + \gamma)n)$  but it is hopeless to get a uniform and sharp upper bound for all  $\mathbf{G}$

### Proof of Shannon's theorem

Let  $\mathbf{G}_k$  be uniformly picked over  $\mathcal{G}_{k,n}$  the set of matrices  $\mathbb{F}_q^{k \times n}$  with rank  $k$

$$\begin{aligned} M &\stackrel{\text{def}}{=} \mathbb{E}_{\mathbf{G}_k} \left( \mathbb{P}_e \left( \mathcal{E}(\mathbf{G}_k, \mathbf{e}) \mid |\mathbf{e}| \leq (\rho + \gamma)n \right) \right) \\ &= \frac{1}{|\mathcal{G}_{k,n}|} \sum_{\mathbf{G} \in \mathcal{G}_{k,n}} \mathbb{P}_e \left( \exists \mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}, \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{e}, |\mathbf{e}|) \mid |\mathbf{e}| \leq (\rho + \gamma)n \right) \\ &\leq \frac{1}{|\mathcal{G}_{k,n}|} \sum_{\mathbf{G} \in \mathcal{G}_{k,n}} \mathbb{P}_e \left( \exists \mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}, \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{e}, (\rho + \gamma)n) \mid |\mathbf{e}| \leq (\rho + \gamma)n \right) \end{aligned}$$

By the union bound, we get

$$M \leq \frac{1}{|\mathcal{G}_{k,n}|} \sum_{\mathbf{G} \in \mathcal{G}_{k,n}} \sum_{\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}} \mathbb{P}_e \left( \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{e}, (\rho + \gamma)n) \mid |\mathbf{e}| \leq (\rho + \gamma)n \right)$$

Therefore,

$$\begin{aligned} M &\leq \frac{1}{|\mathcal{G}_{k,n}|} \sum_{\mathbf{G}} \sum_{\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}} \sum_{\mathbf{x}: |\mathbf{x}| \leq (\rho + \gamma)n} \mathbb{P}_e \left( \mathbf{m}\mathbf{G} \in \mathcal{B}_H(\mathbf{x}, (\rho + \gamma)n) \right) \mathbb{P}_e \left( \mathbf{e} = \mathbf{x} \mid |\mathbf{e}| \leq (\rho + \gamma)n \right) \\ &= \sum_{\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}} \sum_{\mathbf{x}: |\mathbf{x}| \leq (\rho + \gamma)n} \mathbb{P}_{\mathbf{G}_k} \left( \mathbf{m}\mathbf{G}_k \in \mathcal{B}_H(\mathbf{x}, (\rho + \gamma)n) \right) \mathbb{P}_e \left( \mathbf{e} = \mathbf{x} \mid |\mathbf{e}| \leq (\rho + \gamma)n \right) \end{aligned}$$

## Proof of Shannon's Theorem

We have proved: if  $\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}$  then  $\mathbf{m}\mathbf{G}_k$  is uniform over  $\mathbb{F}_q^n \setminus \{0\}$ . Therefore,

$$\mathbb{P}_{\mathbf{G}_k} \left( \mathbf{m}\mathbf{G}_k \in \mathcal{B}_H(\mathbf{x}, (p + \gamma)n) \right) = \frac{|\mathcal{B}_H((p + \gamma)n, n) - 1}{q^n - 1} \leq q^{n(h_q(p + \gamma) - 1)}$$

where the last inequality we used our inequality on the size of Hamming ball. Therefore,

$$\begin{aligned} M &\leq \sum_{\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}} \sum_{\mathbf{x}: |\mathbf{x}| \leq (p + \gamma)n} q^{n(h_q(p + \gamma) - 1)} \mathbb{P}_{\mathbf{e}}(\mathbf{e} = \mathbf{x} \mid |\mathbf{e}| \leq (p + \gamma)n) \\ &= q^{n(h_q(p + \gamma) - 1)} \sum_{\mathbf{m} \in \mathbb{F}_q^k \setminus \{0\}} \mathbb{P}_{\mathbf{e}}(|\mathbf{e}| \leq (p + \gamma)n) \\ &\leq q^{n(h_q(p + \gamma) - 1)} q^k \end{aligned}$$

Finally, since  $k \leq n(1 - h_q(p) - \varepsilon)$  and  $h_q$  is a **decreasing** continuous function over  $\left[0, \frac{p}{q-1}\right]$ , we obtain for  $\gamma$  small enough

$$M = \mathbb{E}_{\mathbf{G}_k} \left( \mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}_k, \mathbf{e}) \mid |\mathbf{e}| \leq (p + \gamma)n \right) \right) \leq q^{n(h_q(p + \gamma) - h_q(p) - \varepsilon)} \leq q^{-n\delta}$$

where  $\delta > 0$  is some constant. Therefore, it exists at least one matrix  $\mathbf{G}_0$  of rank  $k$  in  $\mathbb{F}_q^{k \times n}$  s.t

$$\mathbb{P}_{\mathbf{e}} \left( \mathcal{E}(\mathbf{G}_0, \mathbf{e}) \mid |\mathbf{e}| \leq (p + \gamma)n \right) \leq q^{-n\delta}$$

**Proof of Shannon's theorem:**

Putting everything together we obtain, where  $\mathcal{C}_0$  is the code with generator matrix  $\mathbf{G}_0$ ,

$$\mathbb{P}_{\text{fail}}(\mathcal{C}_0, \mathcal{D}_{\text{ML}}) \leq q^{-n\delta} + 2e^{-\rho n \gamma^2} \leq q^{-\delta' n}$$

for some constant  $\delta' > 0$  showing 1. in Shannon's theorem

It turns out that we have proven (where  $\mathcal{C}$  is a uniform  $[n, k]_q$ -code)

$$\mathbb{E}_{\mathcal{C}} \left( \mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) \right) \leq q^{-\delta' n}$$

→ Therefore, by Markov's inequality:  $\mathbb{P}_{\mathcal{C}} \left( \mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) \geq q^{-\delta' n/2} \right) \leq q^{-\delta' n/2}$

**Conclusion:**

For almost all  $[n, k]_q$ -codes  $\mathcal{C}$  (a proportion  $1 - \frac{1}{q^{\delta' n/2}}$ ), the maximum-likelihood decoder fails with probability exponentially close to 0, *i.e.*,  $\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}_{\text{ML}}) \leq q^{-\delta' n/2}$

## Shannon's theorem for linear codes: negative part

For all  $0 \leq p < \frac{q-1}{q}$  and  $\varepsilon > 0$  it holds that,

2. For all  $\delta > 0$  and  $n$  large enough, and all pair  $(\mathcal{C}, \mathcal{D})$ , where  $\mathcal{C}$  is a linear code with length  $n$  and dimension  $n(1 - h_q(p) + \varepsilon)$ , we have

$$\mathbb{P}_{\text{fail}}(\mathcal{C}, \mathcal{D}) \geq 1 - \delta$$

- The capacity of the  $q\text{SC}(p)$  (according to Lecture 6) is given by  $(1 - h_q(p))$ . Therefore to prove this part of the theorem we can use the negative part of Shannon's theorem from Lecture 6



# RANDOM CODES: A POWERFUL TOOL

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## Fundamental trick:

Suppose that  $\mathcal{C}$  is a uniform  $[n, k]_q$ -code,  $\mathbf{X}$  be some source of randomness and

$$\mathbb{P}_{\mathcal{C}, \mathbf{X}}(\mathcal{C} \text{ verifies some good property } \mathcal{P}) \geq C \quad \text{or} \quad \mathbb{P}_{\mathcal{C}, \mathbf{X}}(\mathcal{C} \text{ verifies some bad property } \mathcal{Q}) \leq \varepsilon$$

Then,

1. It exists at least one  $[n, k]_q$ -code  $\mathcal{C}_0$  verifying the good property with probability at least  $C$ ,

$$\mathbb{P}_{\mathbf{X}}(\mathcal{C}_0 \text{ verifies some good property } \mathcal{P}) \geq C$$

2. The proportion of codes for which the probability of the bad property is  $\geq \sqrt{\varepsilon}$  is  $\leq \sqrt{\varepsilon}$ ,

$$\frac{\#\{c_0: \mathbb{P}_{\mathbf{X}}(c_0 \text{ an } [n, k]_q\text{-code verifying some bad property } \mathcal{Q}) \geq \sqrt{\varepsilon}\}}{\#\{c_0 \text{ be an } [n, k]_q\text{-code}\}} \leq \sqrt{\varepsilon}$$

Proof (nothing else than Markov's inequality):

As  $\mathcal{C}$  is uniform over  $[n, k]_q$ -codes we have by the law of total number,

$$\begin{aligned}\mathbb{P}_{\mathcal{C}, \mathbf{x}}(\mathcal{C} \text{ verifies some property}) &= \frac{1}{M} \sum_{\substack{\mathcal{C}_0 \text{ be an} \\ [n, k]_q\text{-code}}} \mathbb{P}_{\mathbf{x}}(\mathcal{C}_0 \text{ verifies some property}) \\ &= \mathbb{E}_{\mathcal{C}}(\mathbb{P}_{\mathbf{x}}(\mathcal{C} \text{ verifies some property}))\end{aligned}$$

where  $M$  is the number of  $[n, k]_q$ -code. The above sum is enough to conclude

We have proved that we can decode (but without an efficient decoding algorithm) a random code  
up to the channel capacity of  $qSC(p)$

→ We know more things about random codes

**Proposition: weight distribution of random codes**

Let  $\mathcal{C}$  be a random  $[n, k]_q$ -codes where we use the model that  $\mathcal{C}$  admits as parity-check matrix a uniform  $\mathbf{H} \in \mathbb{F}_q^{(n-k) \times n}$ . We have,

$$\forall \ell > 0, \mathbb{E}_{\mathcal{C}} \left( \#\{c \in \mathcal{C} : |c| = \ell\} \right) = \frac{\binom{n}{\ell} (q-1)^\ell}{q^{n-k}}$$

We have proved that we can decode (but without an efficient decoding algorithm) a random code up to the channel capacity of  $qSC(p)$

→ We know more things about random codes

### Proposition: minimum distance of random codes

Let  $\varepsilon > 0$  and  $(\mathcal{C}_n)_{n \in \mathbb{N}}$  be an asymptotic sequence of random  $[n, k]_q$ -codes (whichever of the four models we previously discussed) where  $\frac{k}{n} \xrightarrow[n \rightarrow +\infty]{} R$ . Then,

$$\mathbb{P}_{\mathcal{C}} \left( (1 - \varepsilon)h_q^{-1}(1 - R) \leq \frac{d_{\min}(\mathcal{C}_n)}{n} \leq (1 + \varepsilon)h_q^{-1}(1 - R) \right) \geq 1 - q^{-\alpha n}$$

for some constant  $\alpha > 0$

### Consequence:

Almost all codes  $[n, k]_q$ -codes (via Markov's inequality) with rate  $R \stackrel{\text{def}}{=} k/n$  have a minimum distance given by

$$t_{\text{GV}}(R) \stackrel{\text{def}}{=} h_q^{-1}(1 - R) \cdot n \text{ known as } \text{Gilbert-Varshamov radius}$$

**Proof:**

See Exercise Session

We know that,

- ▶ we can decode with success probability  $> 0$  a random code with rate  $R$  in the  $qSC(p)$  as soon as  $R \leq 1 - h_q(p)$ . But in the  $qSC(p)$  there are  $\approx np$  errors. Notice that

$$R \leq 1 - h_q(p) \iff p \leq nh_q^{-1}(1 - R)$$

## Conclusion:

We can decode a random code of rate  $R$  up to the Hamming distance  $h_q^{-1}(1 - R) \cdot n$

- ▶ random codes with rate  $R$  have minimum distance  $\approx h_q^{-1}(1 - R) \cdot n$ .

## Surprising conclusion:

We can (theoretically, *i.e.*, non-efficiently) decode a random code  $\mathcal{C}_{\text{rand}}$  with probability  $> 0$  as soon as the number of errors is  $\leq d_{\min}(\mathcal{C}_{\text{rand}})$  and not  $d_{\min}(\mathcal{C}_{\text{rand}})/2$

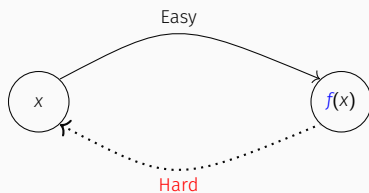
# A LITTLE BIT OF CRYPTOGRAPHY

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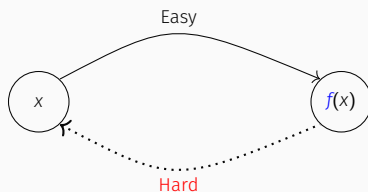


*Find hard problems. . .*

Hard problem: given some function  $f$  such that



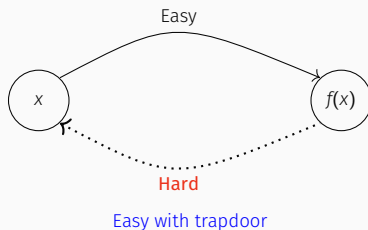
Hard problem: given some function  $f$  such that



- What is Mr. Rodemich number?
- Who is owner of +33 631053595?

→ Can we really do cryptography with **one-way functions**?

Cryptography asks for particular one-way functions: **trapdoor** one-way functions



**Alice** wants to receive secret data

## Public-Key Encryption:

- **Alice** reveals  $f$  to the world but Alice owes **the trapdoor**
- **Bob** wants to share secretly with **Alice** some number 711327: he computes  $f(711327)$
- **Alice** receives  $f(711327)$  and she recovers 711327 while it is hard for everyone else

To build a public-key encryption scheme we need:

- ▶ first, a one-way function  $f$
- ▶ then to find a trapdoor for this function

Public-Key: description of  $f$  ; Secret-Key: its associated trapdoor

Shannon's proof relied on the following decoding problem:

$$\text{Given } \mathbf{y} \stackrel{\text{def}}{=} \mathbf{c} + \mathbf{e} \text{ where } \begin{cases} \mathbf{c} \in \mathcal{C} \text{ with } \mathcal{C} \text{ being a random code} \\ \mathbf{e} \text{ is such that } |\mathbf{e}| \approx t \end{cases},$$

we have to recover the closest codeword from  $\mathbf{y}$

It seems to be a hard problem, Shannon did not give any efficient algorithm to solve this problem!

Shannon only proved that the closest codeword from  $\mathbf{y}$  is  $\mathbf{c}$  if and only if  $\#\mathcal{C}$  is small enough

(capacity condition)

Given  $\mathbf{G} \in \mathbb{F}_q^{k \times n}$ ,

$$f_{\mathbf{G}} : (\mathbf{m}, \mathbf{e}) \in \mathbb{F}_q^k \times \{\mathbf{x} \in \mathbb{F}_q^n : |\mathbf{x}| = t\} \mapsto \mathbf{m}\mathbf{G} + \mathbf{e}$$

- ▶ The knowledge of  $\mathbf{G}$  which defines an  $[n, k]_q$ -code  $\mathcal{C}$  and  $t$  is enough to compute  $f_{\mathbf{G}}$
- ▶ It is easy to compute  $f_{\mathbf{G}}(\mathbf{m}, \mathbf{e})$  (only linear algebra)
- ▶ If  $\mathbf{G}$  has been chosen uniformly, inverting  $f_{\mathbf{G}}$  amounts to decoding a random code at distance  $t$  which is believed to be hard

But we need a trapdoor to build public-key encryptions!

McEliece in '78 had the idea of introducing the following trapdoor:

The underlying code in  $f_G$  is chosen as a code that we know how to decode  
and the quantities which enable to decode form the secret key

→ McEliece proposed in '78 to choose  $G$  as the generator matrix of a *Goppa code*



In Lecture 7 we have studied codes that we know how to decode: *Reed-Solomon* codes

### Berlekamp-Welsh Algorithm:

We can decode  $RS_k(\mathbf{x}, \mathbf{z})$  at any distance  $< \frac{n-k}{2}$

- Public Key: a representation of  $RS_k(\mathbf{x}, \mathbf{z})$  which admits as generator matrix

$$\begin{pmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^k & x_2^k & \cdots & x_n^k \end{pmatrix}$$

- Secret Key:

What is the secret key? Can we give the above matrix as a public key?

In Lecture 7 we have studied codes that we know how to decode: *Reed-Solomon* codes

### Berlekamp-Welsh Algorithm:

We can decode  $RS_k(\mathbf{x}, \mathbf{z})$  at any distance  $< \frac{n-k}{2}$

- Public Key: a representation of  $RS_k(\mathbf{x}, \mathbf{z})$  which admits as generator matrix

$$G_{pk} = S \begin{pmatrix} 1 & 1 & \cdots & 1 \\ x_1 & x_2 & \cdots & x_n \\ x_1^2 & x_2^2 & \cdots & x_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^k & x_2^k & \cdots & x_n^k \end{pmatrix} \text{ where } S \text{ non-singular picks random basis}$$

- Secret Key:  $T = \mathbf{x}$

- ▶ To encrypt a message  $\mathbf{m}$  with the public-key  $G_{pk}$ : compute  $\mathbf{m}G + \mathbf{e}$  where  $|\mathbf{e}| < \frac{n-k}{2}$
- ▶ To decrypt  $\mathbf{m}G_{pk} + \mathbf{e}$  with the knowledge of the secret-key  $T$ : use Berlekamp-Welsh algorithm

But in '92, Sidelnikov and Shestakov have shown how to break this instantiation of McEliece's encryption

→ From the knowledge of  $G_{pk} = S$   $\begin{pmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \\ x_1^2 & x_2^2 & \dots & x_n^2 \\ \vdots & \vdots & \vdots & \vdots \\ x_1^k & x_2^k & \dots & x_n^k \end{pmatrix}$  we can easily recover the secret  $x$

The above attack shows that the security of McEliece's encryption scheme does not strictly rely on the hardness of decoding a random code

*But under which assumptions McEliece's scheme is secure?*

The above attack shows that the security of McEliece's encryption scheme does not strictly rely on the hardness of decoding a random code

*But under which assumptions McEliece's scheme is secure?*

### McEliece security assumption:

We can prove that McEliece's encryption is secure under the following assumptions:

1. It is hard to decode a random code
2. It is hard to distinguish the public-key  $\mathbf{G} \in \mathbb{F}_q^{k \times n}$  and a uniform matrix with the same size

Can we build an encryption scheme whose security is only based on the hardness of decoding a random code?

Yes, a public-key encryption scheme whose security is only based on the hardness of decoding a random code is known since '03:

**Alekhovich's** cryptosystem

- ▶ Lecture notes by Gilles Zémor about Alekhovich's cryptosystem:

<https://www.math.u-bordeaux.fr/~gzemor/alekhovich.pdf>

# EXERCISE SESSION

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