

Why 0-pool detection can be applied to find  $d$  defectives by using a  $d$ -disjunct matrix?

(•) Suppose that  $C_1, C_2, \dots, C_d$  are defectives. Now, for each good item  $C_{d+1}$ ,  $C_{d+1} \notin \bigcup_{i=1}^d C_i$ , there exists a test ( $i^{\text{th}}$  row) such that  $M(i, d+1) = 1$  and  $M(i, j) = 0$  for all  $j = 1, 2, \dots, d$ . Hence, the outcome of the test ( $i^{\text{th}}$  row) is "0", and thus  $C_{d+1}$  is a good item determined by the 0-pool.

Since each good item can be found, these  $d$  defectives are determined. //

### Non-adaptive algorithms for error-model

Due to the experiments, a  $d$ -disjunct matrix or  $d$ -separable matrix may not be able to find all  $d$  defectives or find the wrong  $d$  defectives. Therefore, it takes more effort in designing a matrix in which we can still find all defectives by allowing certain number of errors occurred in experiments.

First, we need some knowledge of Coding Theory.

## Basic Idea in Coding Theory

(To be used in GT with errors occurred in outcomes (Non-adaptive algorithm))

### Definition ( $q$ -ary codes)

A  $q$ -ary code of length  $n$  is a subset of  $(\mathbb{Z}_q)^n$ , i.e.,  $\mathcal{C}$  is a set of vectors (codewords) selected from  $(\mathbb{Z}_q)^n$ . Clearly,  $(\mathbb{Z}_q)^n$  contains  $q^n$  codewords.

In general,  $\mathbb{Z}_q$  is replaced by  $GF(q)$  a finite field of order  $q$  and thus  $q$  is chosen to be a prime power. (If  $q=2$ , then we have a binary code.)

### Definition (Distance)

The distance between two codewords  $\vec{x} = (x_0, x_1, \dots, x_{m-1})$  and  $\vec{y} = (y_0, y_1, \dots, y_{m-1})$

$d(\vec{x}, \vec{y}) = |\{i \mid x_i \neq y_i, i=0, 1, 2, \dots, m-1\}|$  i.e., the number of coordinates which are distinct following the order.

### Definition (Distance of a code)

Let  $\mathcal{C} = \{\vec{x}_1, \vec{x}_2, \dots, \vec{x}_m\}$  be a code. Then the distance of  $\mathcal{C}$ ,

$$d(\mathcal{C}) = \min_{\text{def}} \{d(\vec{x}_i, \vec{x}_j) \mid 1 \leq i < j \leq m\}.$$

For example,  $\mathcal{C} = \{(1, 1, 0, 1, 0, 0, 0), (0, 1, 1, 0, 1, 0, 0), (0, 0, 1, 1, 0, 1, 0),$

$(0, 0, 0, 1, 0, 1), (1, 0, 0, 0, 1, 1, 0), (0, 1, 0, 0, 0, 1, 1), (1, 0, 1, 0, 0, 0, 1)\}$ .  $d(\mathcal{C}) = 4$ .

o) Fact If  $C$  is code (binary) of distance  $d$ , then  $C$  can detect

$\hat{\text{up to}}$   $d-1$  errors and correct  $\hat{\text{up to}}$   $\lfloor \frac{d-1}{2} \rfloor$  errors.

### The fundamental problem of coding theory

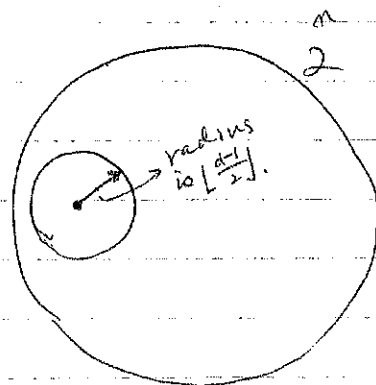
Let  $A_q(n, d)$  denote the maximum number of codewords in a  $q$ -ary code of length  $n$  with code distance  $d$ . (If  $q=2$ , we use  $A(n, d)$  for convenience.)

Example  $A(7, 3) = 16$ .

Fact (Sphere packing bound)

$$A_q(n, d) \leq \frac{q^n}{\sum_{i=0}^{\lfloor \frac{d-1}{2} \rfloor} \binom{n}{i} \cdot (q-1)^i}$$

$$A(n, d) \leq \frac{2^n}{\binom{n}{0} + \binom{n}{1} + \dots + \binom{n}{\lfloor \frac{d-1}{2} \rfloor}}$$



Example  $A(7, 3) \leq \frac{2^7}{\binom{7}{0} + \binom{7}{1}} = 2^4$ .

$$A(7, 3) \geq 16$$

16 codewords

|         |         |
|---------|---------|
| 0000000 | 1111111 |
| 1011000 | 0100111 |
| 0101000 | 1010011 |
| 0010110 | 1101001 |
| 0001011 | 1110100 |
| 1000101 | 0111010 |
| 1100010 | 0011101 |
| 0110001 | 1001110 |

Outcome Vector: Can be recognized as a set,  $V$   
(in error-models)

Denote by  $t_0^V(C) = |C \cap V|$  where  $C$  is a column.

e.g.

|       |   |       |       |       |       |       |       |       |            |
|-------|---|-------|-------|-------|-------|-------|-------|-------|------------|
|       |   | ②     | ③     | 4     | 5     | 6     | $V$   |       | $t_1^V(C)$ |
| $t_1$ |   | 1     | 1     | 0     | 0     | 0     | 1     | {1,2} | =  C ∩ V   |
| $t_2$ | 1 | 0     | 0     |       |       | 0     | 0     | {1,4} |            |
| $t_3$ | 0 | 1     | 0     |       | 0     | 1     | 1     | {2,3} |            |
| $t_4$ | 0 | 0     | 1     |       | 0     | 1     | 1     | {2,6} |            |
|       |   | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |       | {3,4}      |

↑ ↑ ↑ ↑ ↑  
positives

(\*)  $V = C_2 \cup C_3$  (without errors),  $|V|=1$ ,  $|V|>1$  (with errors)

Note that  $t_0^V(C) = |C \cap V|$ ,  $t_1^V(C) = |C \cap V|$ .

$|C \cap V| > 0 \Rightarrow C$  is a negative item  $\Leftarrow (-X)$

- |                  |                  |
|------------------|------------------|
| $t_0^V(C_1) = 1$ | $t_1^V(C_1) = 1$ |
| $t_0^V(C_2) = 0$ | $t_1^V(C_2) = 2$ |
| $t_0^V(C_3) = 0$ | $t_1^V(C_3) = 2$ |
| $t_0^V(C_4) = 1$ | $t_1^V(C_4) = 1$ |
| $t_0^V(C_5) = 1$ | $t_1^V(C_5) = 1$ |
| $t_0^V(C_6) = 0$ | $t_1^V(C_6) = 2$ |

↑  
Negatives  
 $C_1, C_4, C_5$

Two positive res:  $\left\{ \begin{array}{l} \textcircled{2} \textcircled{3} \text{ or} \\ \textcircled{2} \textcircled{6} \text{ or} \\ \textcircled{3} \textcircled{6} \end{array} \right.$

(\*) 如果是 2-disjunct 就不需要留下  $C_2, C_3, C_6$  等待判断。

With one error,

$$V = \left\{ \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + \vec{e} \mid \vec{e} \in \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \right\} \right\} \quad (\langle \mathbb{Z}_2, + \rangle).$$

For example,  $\begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$ . Hence, we may conclude that "6" is positive.

(\*) A stronger disjunct matrix is needed in order to determine the positives.

(\*\*) From Coding Theory point of view, we need to make sure all the outcome vectors are with "distance" from each other. By the idea mentioned above, if we would like to correct one error spot, two vectors must be at least of distance "3".

(\*) With stronger properties, finding such matrices are getting harder, especially if we still ask for less tests.

Item  $\rightarrow$  clone

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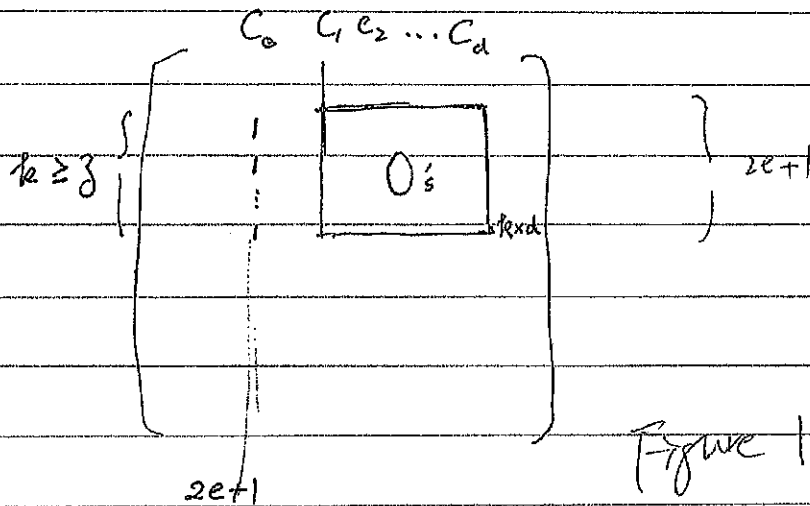
Definition ( $(d; z)$ -disjunct matrix).

A matrix is said to be  $(d; z)$ -disjunct if for any  $d+1$  columns  $C_0, C_1, \dots, C_d$ ,

$$|C_0 \setminus \bigcup_{i=1}^d C_i| \geq z.$$

Note  $(d; 1)$ -disjunct  $\approx$   $d$ -disjunct.

(\*) There exist at least  $z$  rows in each of which  $C_0$  has a "1"-entry and every  $C_i, 1 \leq i \leq d$ , has a "0"-entry.



Theorem A  $(d; z)$ -disjunct matrix can be applied to identify up-to- $d$  positives with at most  $e$  errors.

Proof We remark that the errors occur on the conclusion of tests, i.e., the outcome vector (as a codeword) has at most  $e$  errors. (Due the fact that errors are possible, we shall have a set of possible outcomes  $\checkmark$  instead of just one outcome vector.)

Now, assume the number of errors is  $e$ . For each negative clone  $\bar{C}$ , by definition, there exist at least  $2e+1$  rows intersecting  $\bar{C}$  but none of  $D$  (the set of positives). This implies that for each clone  $\bar{C}$  or  $\bar{C}^T$ ,

$$t_0^V(C^-) \geq (2e+1) - e, \text{ and } t_0^V(C^+) \leq e. \quad 9$$

说明:  $(t_0^V(C^*) \stackrel{\text{def}}{=} |C^* \setminus V|) \rightarrow$  See 5' for examples.

由於 Outcome vector 是所有 positive clones 的  
 交集; 如果用  $(d; 2e+1)$ -disjunct 矩陣來測試的  
 話, 對於所有 positive clone  $C^+$ ,  $t_1^V(C^+) \geq 2e+1$  (沒  
 有任何 Errors 產生的情況)。這可以從上頁 Figure 1

看出來: 把  $C_0$  當成  $C$  (positive),  $|V| \geq 2e+1$ 。

如果把 positives 都放入  $\{C_1, C_2, \dots, C_d\}$  而  $C_0$  為  
 negative, 則  $t_0^V(C^-) \geq 2e+1$ 。

於是存在  $e$  個錯誤的情況下  $t_0^V(C^-) \geq e+1$ ;

另外  $t_0^V(C^+) = 0$  (沒有錯誤), 存在  $e$  個錯誤  
 $\parallel$   
 $|C^+ \setminus V| = |\emptyset|$

的情況下,  $t_0^V(C^+) \leq e$ 。

上述的說明也提供了 Linear Time Decoding Algorithm

(on  $|N|$ )



每個 clone 都測試一次。

(\*) How to construct  $(d; z)$ -disjunct matrices?

(\*) We can use a  $d$ -disjunct matrix to identify up-to- $d$  positive clones. (Respectively, use a  $(d; 2e+1)$ -disjunct matrix for error-models with at most  $e$  errors.)

Theorem If a set of  $n$  clones which contains at most  $d$  positive then a  $d$ -disjunct matrix can be applied to identify the positives. Moreover, the decoding algorithm is linear complexity of

Proof. The proof follows by evaluating  $t_0^V(C)$  for each clone  $C$ . ( $V$  is the outcome vector.) We remark here that  
 $t_0^V(C) = 0$  if  $C$  is positive and  $t_0^V(C) \geq 1$  if  $C$  is negative.  
 ( $t_0^V(C) = |C \setminus V|$ .)

(\*) If there are at most  $e$  errors, then  $t_0^V(C^+) \leq e$  and  $t_0^V(C^-) \geq e+1$ .

(\*) Algorithm (Clone Selection  $(N, V, D, e)$ )  $\rightarrow$  possible # of error

- 1 for each clone  $C \in N$ , ( $D \leftarrow \emptyset$ )
- 2 compute  $t_0^V(C)$
- 3 if  $t_0^V(C) \leq e$
- 4 then  $D \leftarrow D \cup \{C\}$
- 5 return

$$V = \bigcup_{C \text{ positive}} C$$

(\*) 定理 (Clone Selection  $(N, V, D, 0)$ )

(\*) Key point If  $C$  is positive, then  $t_0^V(C) = 0$ ; and ( $V$  is the outcome vector.)  
 $C$  is negative, then  $t_0^V(C) \geq 1$ .



(Note)

If errors occur, then an adaptive algorithm is getting much more complicated than using a non-adaptive algorithm.

The reason is very simple, since we have no control on the occurrence of errors. In a word, it may occur in an early stage, so does in later stages.

(\*) 如果我們可以確定錯誤的產生是來自“過多”的 Items

一起測試，則總 Tests 的個數就不會太多；換句話說，

我們可以在每一次測試的 pool 放入不超過可能產生的

量，也可以解決這個問題。

(\*\*) 如果是從 Game 的角度來看這個問題，那麼適當引進

新的 “Adaptive algorithms” 是可以獲得較好的結果。

口頭報告的順序 (書面報告繳交截止日期 Jan. 18, 2022.)

1. A study of fake coins problem

Dec. 7, 呂欣芳 ; Dec. 21, 賴冠宇

2. Determine  $M(2, n)$

Dec. 7, 陳建弘 ; Dec. 21, 郭傑森

3. Generalized binary splitting algorithm

Dec. 7, 官梓甸 ; Dec. 28, 賴淳偉

4. A study of half-size induced subgraph of a bipartite graph

Dec. 14, 楊珈禎 ; Dec. 28, 曾永來

5. Use probabilistic method to construct disjoint matrices

Dec. 14, 黃伯丞 ; Dec. 28, 楊子儀

6. Find the maximum size of a bipartite graph which is  $C_4$ -free

Dec. 14, 陳安德 ; Jan. 4, 陳惟彥

7. How to find a hidden subgraph of a complete graph

Dec. 21, 楊子賢 ; Jan. 4, 溫佳音