# 応用数学特論Ⅱ (集中講義)

#### Day 5 Cyclic Designs and Their Applications

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#### Outline

- 1 Binary sequences with optimal autocorrelation and cyclic designs
- 2 Statistical designs for fMRI experiments and cyclic almost orthogonal arrays (CAOA)
- CAOAs, optimal sequences, and ADSs

# Binary periodic sequences

#### Definition (binary periodic sequences with period n)

A binary sequence (系列)  $\mathbf{s}=(s_0,s_1,\ldots,\mathbf{g}_{n-1},\mathbf{g}_n,\mathbf{g}_{n+1},\ldots)$  is said to be periodic with period (周期) n if

$$s_i = s_{i+n}$$
 for any  $i \ge 0$ .

- A binary periodic sequence s with period n can be seen as a binary string of length n, say,  $\mathbf{s} = (s_t) \in \{0,1\}^n$ .
- In this lecture, we say s is a binary sequence of length n.

# Autocorrelation magnitude of binary sequences

#### Definition (Autocorrelation of binary sequences)

(n=4 a (31))

The periodic autocorrelation (周期的自己相関関数) of a binary sequence  $\mathbf{s}=(s_t)\in\{0,1\}^n$  at shift w is defined by

where the subscript of  $s_{t+w}$  is reduced by modulo n.

- The maximum absolute value of the off-peak autocorrelation  $\max_{w\neq 0} |\rho_{\mathbf{s}}(w)|$  is called the autocorrelation magnitude (自己相関のマグニチュード) of s.
- Sequences with low autocorrelation magnitudes are desired.

Example: > Jupyper Notebook

# Perfect sequence

#### Definition (Perfect sequences)

A binary sequence  $\mathbf{s} = (s_t) \in \{0,1\}^n$  with autocorrelation magnitude 0 is called a perfect sequence (完全系列).

#### **Proposition**

A binary sequence of length n is a perfect sequence  $\implies n \equiv 0 \pmod{4}$ .

#### Example (n=4)

 ${f s}=(1110)$  is a perfect sequence. This is the only known binary perfect sequence (up to equivalence of cyclic shift).

# Binary sequences with optimal autocorrelation magnitude

- 1 For  $n \equiv 0 \pmod 4$ ,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| \geq 0$ . There is only one example (perfect sequence) with  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 0$ . So, it is natural to consider  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 4 \iff \rho_{\mathbf{s}}(w) \in \{0,4\}$  or  $\{0,-4\}$  for all  $1 \leq w \leq n-1$ ; in this case, the sequence is said to have optimal autocorrelation.
- 2 For  $n \equiv 3 \pmod 4$ ,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| \ge 1$ . Moreover,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 1 \iff \rho_{\mathbf{s}}(w) = -1$  for all  $1 \le w \le n-1$ ; in this case, the sequence is said to have optimal autocorrelation.
- 3 For  $n \equiv 1 \pmod 4$ ,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| \geq 1$ . But there is some evidence that there is no binary sequence of length n > 13 with  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 1$ . So, it is natural to consider  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 3 \iff \rho_{\mathbf{s}}(w) \in \{1, -3\}$  for all  $1 \leq w \leq n 1$ ; in this case, the sequence is said to have optimal autocorrelation.
- **4** For  $n \equiv 2 \pmod{4}$ ,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| \geq 2$ . Moreover,  $\max_{w \neq 0} |\rho_{\mathbf{s}}(w)| = 2 \iff \rho_{\mathbf{s}}(w) \in \{2, -2\}$  for all  $1 \leq w \leq n 1$ ; in this case, the sequence is said to have optimal autocorrelation.

# Example of sequences with optimal autocorrelation

#### Example (A bad example)

- $\mathbf{s} = (1101000101)$
- For w = 5, we have  $(s_{t+w} s_t)_t = (-1, -1, 1, 1, 1, 1, 1, -1, 1, -1)$ .

$$\rho_{\mathbf{s}}(w) = \sum_{t=0}^{n-1} (-1)^{s_{t+w}-s_t} = -10 \notin \{2, -2\}$$

#### Example (A good example)

- $\mathbf{s} = (1000101101)$
- For w = 5, we have  $(s_{t+w} s_t)_t = (-1, 1, 1, 0, 0, 1, -1, -1, 0, 0)$ .

# Optimal binary sequences with one valued autocorrelation

- 1 For  $n \equiv 0 \pmod{4}$ , there are only two examples (n = 8, 40) with  $\rho_{\mathbf{s}}(w) = 4$  for all  $1 \le w \le n 1$ . It is proved that no other exists. <sup>1</sup>
- 2 For  $n \equiv 3 \pmod 4$ , there are infinite many examples with  $\rho_{\mathbf{s}}(w) = -1$  for all  $1 \le w \le n 1$  (see the next slide).
- 3 For  $n \equiv 1 \pmod 4$ , there are only two examples (n=5,13) with  $\rho_{\mathbf{s}}(w)=1$  for all  $1 \leq w \leq n-1$ . It is conjectured that no other exists (verified true for 13 < n < 101701 except possibly for  $n \in \{29525, 30013, 34061\}$ ).
- 4 For  $n \equiv 2 \pmod 4$ , there is only one examples (n=6) with  $\rho_{\mathbf{s}}(w) = 2$  for all  $1 \le w \le n-1$ . It is conjectured that no other exists (verified true for 6 < n < 33895686).

Example: > Jupyper Notebook

<sup>&</sup>lt;sup>1</sup>X. Niu, H. Cao, and K. Feng. Binary periodic sequences with 2-level autocorrelation values. Discrete Math. 343(3): 111723 (2020).

# Combinatorial designs and optimal binary sequences

- Let  ${\bf s}$  be a binary sequence of length n.
- Let supp(s) denote the support of s, i.e.,  $supp(s) = \{1 \le i \le n-1 : s_i = 1\}.$

#### Theorem (Difference sets (DS) & almost difference sets (ADS) $\iff$ optimal sequences)

- For  $n \equiv 3 \pmod{4}$ ,  $\rho_{\mathbf{s}}(w) = -1$  for all  $1 \le w \le n-1 \iff \operatorname{supp}(\mathbf{s})$  is an (n, (n+1)/2, (n+1)/4) or (n, (n-1)/2, (n-3)/4) DS in  $\mathbb{Z}_n$ .
- 2 For  $n \equiv 1 \pmod{4}$ ,  $\rho_{\mathbf{s}}(w) \in \{1, -3\}$  for all  $1 \leq w \leq n 1 \iff \operatorname{supp}(\mathbf{s})$  is an  $(n, k, k (n+3)/4, (n-k)k (n-1)^2/4)$  ADS in  $\mathbb{Z}_n$ .
- 3 For  $n \equiv 0 \pmod{4}$ ,  $\rho_{\mathbf{s}}(w) \in \{0, -4\}$  for all  $1 \leq w \leq n 1 \iff \operatorname{supp}(\mathbf{s})$  is an (n, k, k (n + 4)/4, (n k)k n(n 1)/4) ADS in  $\mathbb{Z}_n$ .
- For  $n \equiv 2 \pmod{4}$ ,  $\rho_{\mathbf{s}}(w) \in \{2, -2\}$  for all  $1 \le w \le n 1 \iff \operatorname{supp}(\mathbf{s})$  is an (n, k, k (n+2)/4, (n-k)k (n-1)(n-2)/4) ADS in  $\mathbb{Z}_n$ .

# Cyclic difference sets

• For  $D=\{b_1,\ldots,b_k\}\subseteq \mathbb{Z}_n$  and nonzero  $x\in \mathbb{Z}_n$ ,

$$\Delta_x(D) := \{(b_i, b_j) \in D \times D : b_i - b_j = x\}.$$

$$(n,k,\lambda)$$

# Cyclic difference set (DS) - Difference family (DF) with 1 block

A k-subset  $D \subseteq \mathbb{Z}_n$  is an  $(n, k, \lambda)$  difference set (DS) in  $\mathbb{Z}_n$  if  $|\Delta_x(D)| = \lambda$  for any nonzero  $x \in \mathbb{Z}_n$ .

- Paley-type DS: (4m-1,2m-1,m-1)-DS [Hadamard matrix  $H_{4m}$ ]
- Singer DS:  $(\frac{q^{m+1}-1}{q-1}, \frac{q^m-1}{q-1}, \frac{q^{m-1}-1}{q-1})$ -DS [finite projective geometry  $PG(m, \mathbb{F}_q)$ ]

# Cyclic almost difference sets: Definition

• For  $D=\{b_1,\ldots,b_k\}\subseteq \mathbb{Z}_n$  and nonzero  $x\in \mathbb{Z}_n$ ,

$$\Delta_x(D) := \{(b_i, b_j) \in D \times D : b_i - b_j = x\}.$$

# Cyclic almost difference set (ADS)



A k-subset  $D\subseteq \mathbb{Z}_n$  is an  $(n,k,\lambda,t)$  almost difference set (ADS) in  $\mathbb{Z}_n$  if  $|\Delta_x(D)|=\lambda$  for any  $x\in X$  and  $|\Delta_y(D)|=\lambda+1$  for any  $y\in Y$ , where  $X\cup Y=\mathbb{Z}_n\setminus\{0\}$  with |X|=t.

$$(n,k,\lambda)$$
-DS  $\Leftrightarrow$   $(n,k,\lambda,n-1)$ -APS

- Paley-type DS: (4m 1, 2m 1, m 1, 4m 2)-ADS.
- In this lecture, I will focus on (4m-2, 2m-1, m-1, 3m-2)-ADS.
- Motivated by sequences and (recent work on) experimental designs.

# Cyclic almost difference sets: Example

#### Example: (10, 5, 2, 7)-ADS in $\mathbb{Z}_{10}$

- $D = \{0, 4, 6, 7, 9\} \subseteq \mathbb{Z}_{10}$ .
- $X = \{\pm 1, \pm 2, \pm 4, 5\}, Y = \{\pm 3\}.$

$$\lambda = 2$$

$$\lambda + 1 = 3$$

$$\Delta_2(D) = \{(6,4), (9,7)\},$$

$$\Delta_3(D) = \{(7,4), (9,6), (0,7)\},$$

$$\Delta_4(D) = \{(4,0), (0,6)\},$$

$$\Delta_5(D) = \{(9,4), (4,9)\}.$$

 $\Delta_1(D) = \{(0,9), (7,6)\},\$ 

$$\triangle_6(D) = \triangle_4(D)$$

# Cyclic almost difference sets: Constructions

#### Known constructions for cyclic ADS with $n \equiv 2 \pmod{4}$ and k = n/2

There exits an  $(n, \frac{n}{2}, \frac{n-2}{4}, \frac{3n-2}{4})$ -ADS for the following n:

- (SLCE<sup>2 3</sup>) n = q 1, where  $q \equiv 3 \pmod{4}$  is a prime power;
- 2 (DHM<sup>4</sup>) n=2p, where  $p\equiv 5\pmod 8$  is a prime and p-1 or p-4 is a perfect square.
- **3**  $n \in \{34, 38, 50\}$  by computer search.

 $<sup>^{2}</sup>$ V. M. Sidelnikov: Some k-valued pseudo-random sequences and nearly equidistant codes. Probl. Peredachi Inf. 5(1):16–22 (1969).

<sup>&</sup>lt;sup>3</sup>A. Lempel, M. Cohn, W. Eastman. A class of balanced binary sequences with optimal autocorrelation properties. IEEE Trans. Inform. Theory, IT-23 (1), 38–42 (1977).

<sup>&</sup>lt;sup>4</sup>C. Ding, T. Helleseth, H. Martinsen: New families of binary sequences with optimal three-level autocorrelation. IEEE Trans. Inform. Theory, 47(1): 428–433 (2001).

SLCE sequences
$$f(x) = \{g^*, g', ..., g^{\ell-2}\}$$
•  $g$ : generator of  $\mathbb{F}_q^*$ 

- $C_1^{(2,q)} = \{g^{2t+1} : 0 \le t < (q-1)/2\}.$

# $C_{n}^{(2,k)} = \{g', g^{2}, g^{4}, ..., g^{3-3}\}$ = 版上の平方元の集台(Swlgpp)

#### Theorem (SLCE sequence)

Let  $q \equiv 3 \pmod{4}$  be a prime power and g be a primitive element of  $\mathbb{F}_q$ . Let D be the subset of  $\mathbb{Z}_{a-1}$  defined by  $\log_a(C_1^{(2,q)}-1)$ , where  $\log_a$  denotes the discrete logarithm in  $\mathbb{F}_a$  to the base g. Then D is a  $(q-1, \frac{q-1}{2}, \frac{q-3}{4}, \frac{3q-5}{4})$  ADS in  $\mathbb{Z}_{q-1}$ . In other words, the corresponding binary sequence of D of length q-1 is perfect and balanced.

The admissible prime powers q < 100 for SLCE sequences are

# An example of SLCE sequences

Table: The cyclic group  $\mathbb{F}_{11}^*$  generated by g=2

i	0	1	2	3	4	5	6	7	8	9
$2^i \mod 11$	1	2	4	8	5	10	9	7	3	6

#### Example (A SLCE type (10, 5, 2, 7) ADS in $\mathbb{Z}_{10}$ )

Take g=2 as a generator of  $\mathbb{F}_{11}^*$ . Then

$$C_1^{(2)} = \{2^1, 2^3, 2^5, 2^7, 2^9\} \equiv \{2, 8, 10, 7, 6\} \pmod{11}.$$

Let

$$D = \log_2(C_1^{(2)} - 1) = \log_2\{1, 7, 9, 6, 5\} = \{0, 7, 6, 9, 4\},$$

where  $\log_2$  denotes the discrete logarithm in  $\mathbb{F}_{11}$  to the base 2.

# **DHM** sequences

$$C_i^{(4,p)} = \left\{ g^{4t+i} : 0 \le t < \frac{p-1}{4} \right\}$$

#### Theorem (DHM sequences)

Let n be a positive integer such that n=2p with prime  $p\equiv 5\pmod 8$ . Let  $i,j,l\in\{0,1,2,3\}$  be three distinct integers, and let

$$C_0 = C_i^{(4,p)} \cup C_j^{(4,p)}$$
 and  $C_1 = C_j^{(4,p)} \cup C_l^{(4,p)}$ .

Then,

$$D = (\{0\} \times C_0) \cup (\{1\} \times C_1) \cup \{(0,0)\}$$

is an  $(n, \frac{n}{2}, \frac{n-2}{4}, \frac{3n-2}{4})$  ADS in  $\mathbb{Z}_2 \times \mathbb{Z}_p$  (isomorphic to  $\mathbb{Z}_{2p}$ ) if the generator of  $\mathbb{Z}_p^*$  is properly chosen for the cyclotomic classes and

- **1** p-4 is a perfect square and  $(i,j,l) \in \{(0,1,3),(0,2,3),(1,2,0),(1,3,0)\}$  or

## An example of DHM sequences

Table: The cyclic group  $\mathbb{F}_5^*$  generated by g=3

i	0	1	2	3
$3^i \bmod 5$	1	3	4	2

#### Example (A DHM type (10, 5, 2, 7) ADS in $\mathbb{Z}_{10}$ )

Take 
$$g=3$$
 as a generator of  $\mathbb{F}_5^*$ . Let  $C_0=C_0^{(4)}\cup C_1^{(4)}=\{1,3\}$  and  $C_1=C_1^{(4)}\cup C_2^{(4)}=\{3,4\}$ , and let  $D=\left(\{0\}\times C_0\right)\cup\left(\{1\}\times C_1\right)\cup\left\{(0,0)\right\}$ . Then,

$$D=\{(0,1),(0,3),(1,3),(1,4),(0,0)\}\subseteq \mathbb{Z}_2 imes \mathbb{Z}_5 \cong \mathbb{Z}_{10}.$$

Equivalently, 
$$D = \{6, 8, 3, 9, 0\} \subseteq \mathbb{Z}_{10}$$
.  $(0, \frac{1}{6}) \in \mathbb{Z}_2 \times \mathbb{Z}_3 \iff \{j+1\}$  (j.ed)

# Existence for (n = 4m - 2, 2m - 1, m - 1, 3m - 2)-ADS with small n

- (SLCE) n = q 1, where  $q \equiv 3 \pmod{4}$  is a prime power;
- (DHM) n=2p, where  $p\equiv 5\pmod 8$  is a prime and p-1 or p-4 is a perfect square.
- $n \in \{34, 38, 50\}$  by computer search.

n	6	10	14	18	22	26	30	34	38	42	46
Construction	S	S,D	Æ	S	S	S,D	S	PC	PC	S	S
n	50	54	58	62	66	70	74	78	82	[86, 98]	
Construction	PC	∄?	S,D	?	S	S	D	S	S	?	

→ Homework

#### Outline

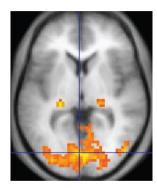
- ① Binary sequences with optimal autocorrelation and cyclic designs
- 2 Statistical designs for fMRI experiments and cyclic almost orthogonal arrays (CAOA) Statistical models and designs for fMRI experiments Statistical optimality for designs
- 3 CAOAs, optimal sequences, and ADSs

#### Outline

- ① Binary sequences with optimal autocorrelation and cyclic designs
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# fMRI experiments

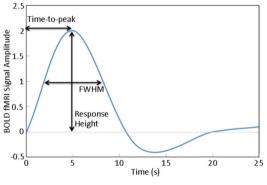
- Functional magnetic resonance imaging (fMRI) is a way to study neural correlates of consciousness involving perception, memory, learning, thinking, and affection by measuring hemodynamic response to mental stimuli.
- An fMRI experiment measures brain activity by detecting changes associated with blood flow.
- In an fMRI experiment, the experimental subject is asked to participate in mental tasks in response to the stimuli, while the subject's brain is scanned by a magnetic resonance (MR) scanner.



An fMRI image from https://en.wikipedia.org/wiki/Functional\_magnetic\_resonance\_imaging

#### **HRFs**

- The MR signal changes following stimuli are of great interests.
- Hemodynamic response functions (HRF) are typically used for describing the signal changes.



An example of HRF

from: https://doi.org/10.1002/mrm.27146

# Model assumption for statistical analysis

Time series data

- In an fMRI experiment, each observation at a constant time interval is supposed to be affected by not only the current stimulus but also the preceding stimuli.
- A mental stimulus (e.g., a 1.5-second flickering image) is presented to a subject during n time points in the experiment.
- The HRF completely returns to baseline after k time points.

Next we review the statistical model (linear regression model) for an experiment with a single type of stimulus to estimate hemodynamic response functions (HRFs).

# Linear model for estimating an HRF

The linear model for estimating an HRF can be expressed as follows:

$$y_i = \gamma + x_i h_1 + x_{i-1} h_2 + \dots + x_{i-k+1} h_k + \varepsilon_i$$
, for  $i = 1, 2, \dots, n$ ,

- $y_i$ : measurement obtained by an fMRI scanner at the *i*th time point.
- $\gamma$ : nuisance parameter.
- $h_j$ : unknown height (magnitude) of the HRF at the (j-1)th time point.
- $x_{i-k+1} \in \{0,1\}$  s.t.  $x_{i-k+1} = 1$  if  $h_j$  contributes to  $y_i$  and  $x_{i-k+1} = 0$  otherwise.
- $\varepsilon_i$ : Gaussian noise with mean 0 and variance  $\sigma^2$ .

#### Moreover,

• 
$$x_l = x_{n+l}$$
 for  $l \leq 0$ . (cf. [Cheng and Kao, 2015]<sup>5</sup>)  $(\star)$ 

<sup>&</sup>lt;sup>5</sup>C. S. Cheng, M. H. Kao, Optimal experimental designs for fMRI via circulant biased weighing designs, Ann. Stat., 43(6): 2565–2587 (2015).

# Linear model for estimating an HRF: matrix form

$$y_{1} = \gamma + x_{1}h_{1} + x_{0}h_{2} + x_{-1}h_{3} + \dots + x_{2-k}h_{k} + \varepsilon_{1},$$

$$y_{2} = \gamma + x_{2}h_{1} + x_{1}h_{2} + x_{0}h_{3} + \dots + x_{3-k}h_{k} + \varepsilon_{2},$$

$$y_{3} = \gamma + x_{3}h_{1} + x_{2}h_{3} + x_{1}h_{3} + \dots + x_{4-k}h_{k} + \varepsilon_{3},$$

$$\vdots$$

$$y_{n} = \gamma + x_{n}h_{1} + x_{n-1}h_{2} + x_{n-2}h_{3} + \dots + x_{n-k+1}h_{k} + \varepsilon_{k}.$$

#### Matrix form of the model

$$\mathbf{y} = \gamma \mathbf{1}_n + \mathbf{X}\mathbf{h} + \boldsymbol{\varepsilon},$$

- $\mathbf{y} = (y_1, \dots, y_n)^{\mathsf{T}}$ ,  $\mathbf{h} = (h_1, \dots, h_k)^{\mathsf{T}}$ ,  $\boldsymbol{\varepsilon} = (\varepsilon_1, \dots, \varepsilon_n)^{\mathsf{T}}$ ,  $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2 \mathbf{I}_n)$ .
- $\mathbf{X} = [\mathbf{X}_{(1)}, \dots, \mathbf{X}_{(k)}] = (x_{ij}) \in \{0, 1\}^{n \times k}$ : design matrix.

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# Design matrix for the linear model

$$\mathbf{X} = \begin{bmatrix} x_1 & x_0 & x_{-1} & \cdots & x_{2-k} \\ x_2 & x_1 & x_0 & \cdots & x_{3-k} \\ x_3 & x_2 & x_1 & \cdots & x_{4-k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_n & x_{n-1} & x_{n-2} & \cdots & x_{n-k+1} \end{bmatrix} =: \begin{bmatrix} \mathbf{X}_{(1)}, \dots, \mathbf{X}_{(k)} \end{bmatrix} \in \{0, 1\}^{n \times k}$$

- $x_l = x_{n+l}$  for  $l \le 0$ . By  $(\star)$ ,  $\mathbf{X}$  is circulant, i.e.  $\mathbf{X}_{(j)} = \mathbf{C}^{j-1}\mathbf{X}_{(1)}$  for  $1 \le j \le k$ , where  $\mathbf{C} = \begin{bmatrix} \mathbf{0}^\top & 1 \\ \mathbf{I}_{n-1} & \mathbf{0} \end{bmatrix}$ .

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#### Information matrix for the linear model

- A:  $k \times n$   $\{0,1\}$  circulant array. ( $\mathbf{X} = \mathbf{A}^{\top}$ : design matrix)
- Let  $\tilde{\mathbf{X}} = (\mathbf{J} 2\mathbf{A})^{\top} (\leftarrow \text{ a } \pm 1 \text{ matrix})$
- Let  $\mathbf{M}(\mathbf{A}) = \tilde{\mathbf{X}}^{\top} \left( \mathbf{I}_n \frac{1}{n} \mathbf{J}_n \right) \tilde{\mathbf{X}}$ . ( $\leftarrow$  information matrix for the  $\pm 1$  matrix)

The information matrix for estimating h is given as

$$\mathbf{M}_{\mathbf{X}} = \mathbf{X}^{\top} \left( \mathbf{I}_n - \frac{1}{n} \mathbf{J}_n \right) \mathbf{X} = \frac{1}{4} \mathbf{M}(\mathbf{A}),$$

where 
$$\mathbf{J}_n = \mathbf{1}_n \mathbf{1}_n^{ op}$$
. For convenience, we consider  $\mathbf{M}(\mathbf{A})$  instead of  $\mathbf{M}_{\mathbf{X}}$ .

## Design matrix: an example

• n = 10. k = 5.

$$\mathbf{X}^{\top} = \begin{bmatrix} 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}, \qquad \mathbf{M}_{\mathbf{X}} = \frac{1}{2} \begin{bmatrix} 5 & -1 & -1 & 1 & -1 \\ -1 & 5 & -1 & -1 & 1 \\ -1 & -1 & 5 & -1 & -1 \\ 1 & -1 & -1 & 5 & -1 \\ -1 & 1 & -1 & -1 & 5 \end{bmatrix}$$

$$\tilde{\mathbf{X}}^{\top} = \begin{bmatrix} - & + & + & - & + & + & - & + \\ - & - & + & + & - & + & + & - & + \\ - & - & - & + & + & - & + & + & - \\ - & + & - & - & - & + & + & - & + & + \end{bmatrix}, \qquad \mathbf{M}_{\mathbf{X}} = \begin{bmatrix} 10 & -2 & -2 & 2 & -2 \\ -2 & 10 & -2 & -2 & 2 \\ -2 & -2 & 10 & -2 & -2 \\ 2 & -2 & -2 & 10 & -2 \\ -2 & 2 & -2 & -2 & 10 \end{bmatrix}$$

$$\mathbf{M_X} = \frac{1}{2} \begin{vmatrix} 5 & -1 & -1 & 1 & -1 \\ -1 & 5 & -1 & -1 & 1 \\ -1 & -1 & 5 & -1 & -1 \\ 1 & -1 & -1 & 5 & -1 \\ -1 & 1 & -1 & -1 & 5 \end{vmatrix}$$

$$\mathbf{M_X} = \begin{vmatrix} 10 & -2 & -2 & 2 & -2 \\ -2 & 10 & -2 & -2 & 2 \\ -2 & -2 & 10 & -2 & -2 \\ 2 & -2 & -2 & 10 & -2 \\ -2 & 2 & -2 & -2 & 10 \end{vmatrix}$$

#### Definition of CAOAs

#### Definition (Circulant almost orthogonal arrays; CAOAs)

A binary circulant  $k \times n$  array  $\mathbf{A}$  is a circulant almost orthogonal array (CAOA) with parameter (n,k,2,t,b), if in any  $t \times n$  subarray of  $\mathbf{A}$  it holds that  $|\lambda(\mathbf{a}_1) - \lambda(\mathbf{a}_2)| \leq b$  for any distinct  $\mathbf{a}_1, \mathbf{a}_2 \in \{0,1\}^t$ , where  $\lambda(\mathbf{a})$  is the frequency of  $\mathbf{a}$  as column vectors. [Lin, et al., 2017] <sup>6</sup>

#### Example (CAOA(10, 5, 2, 2, 1))

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

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<sup>&</sup>lt;sup>6</sup>Y. L. Lin, F. K. H. Phoa, M. H. Kao. Optimal design of fMRI experiments using circulant (almost-) orthogonal arrays. Ann. Stat.,45(6): 2483–2510 (2017).

# $\mathsf{CAOA}(n, k, 2, 2, b) \text{ for } n \not\equiv 2 \pmod{4}$

- When  $n \equiv 0 \pmod{4}$ 
  - ▶ A CAOA(n, k, 2, 2, b = 0) is equivalent to a circulant partial Hadamard design<sup>7</sup> 0-H  $(k \times n)$ .
  - ► Construction via H-sequence, Paley difference sets <sup>8</sup>.
  - ► CAOA(4u, 14, 2, 2, 0) for any  $u \ge 9$  [Lin, et al., 2017] (by a recursive construction).
- When  $n \equiv 1, 3 \pmod{4}$ ,
  - Construction via extended H-sequences.
  - Construction by difference variance algorithms (DVA).
- When  $n \equiv 3 \pmod{4}$ , a CAOA(n, n, 2, 2, 1) exists if:
  - $n \equiv 3 \pmod{4}$  and n is a prime. (via Paley difference sets)
  - ightharpoonup n=p(p+2) where p and p+2 are both odd primes. (via twin prime difference sets)
  - ▶  $n = 2^m 1$  where  $m \ge 2$ . (via Singer difference sets)

盧 暁南 (Xiao-Nan LU)

<sup>&</sup>lt;sup>7</sup>Y. L. Lin, F. K. H. Phoa, M. H. Kao. Circulant partial Hadamard matrices: construction via general difference sets and its application to fMRI experiments. Stat. Sinica, 27(4): 1715–1724 (2017).

<sup>&</sup>lt;sup>8</sup>C. S. Cheng, M. H. Kao. Optimal experimental designs for fMRI via circulant biased weighing designs. Ann. Stat., 43(6): 2565–2587 (2015).

# $\mathsf{CAOA}(n, k, 2, 2, b) \text{ for } n \equiv 2 \pmod{4}$

- - $ightharpoonup \exists T_2\text{-CAOA}(2n, n, 2, 2, 1)$  for all odd prime n [Lin, et al., 2017] (using Paley DS).

# Definition $(T_1$ -, $T_2$ -, $T_3$ -, $T_3^*$ -CAOA)

- **1** A is a  $T_1$ -CAOA if  $\mathbf{M}(\mathbf{A}) = (n-2)\mathbf{I}_k + 2\mathbf{J}_k$ ,
- **2** A is a  $T_2$ -CAOA if  $\mathbf{M}(\mathbf{A}) = (n+2)\mathbf{I}_k 2\mathbf{J}_k$ ,
- **3** A is a  $T_3$ -CAOA if A is neither  $T_1$  nor  $T_2$ -CAOA.

#### **Problems**

- Which type of CAOA is better (best = optimal)?
- **2** How large k can be for given  $n \equiv 2 \pmod{4}$ ?
- 3 How do we construct such CAOAs?

#### Outline

- ① Binary sequences with optimal autocorrelation and cyclic designs
- 2 Statistical designs for fMRI experiments and cyclic almost orthogonal arrays (CAOA) Statistical models and designs for fMRI experiments Statistical optimality for designs
- CAOAs, optimal sequences, and ADSs

# Some well-known optimality criteria

- Roughly speaking, optimality criteria are functionals of the eigenvalues of the information matrix  $\mathbf{M}$ .
- M: non-negative definite symmetric matrix of rank k with eigenvalues  $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k$ .
- D-optimality (determinant): minimize  $\det(\mathbf{M}^{-1})$ , i.e., maximize  $\prod_{i=1}^k \lambda_i$ .
- A-optimality (trace or "average"): minimize  $\operatorname{tr}(\mathbf{M}^{-1})$ , i.e., minimize  $\sum_{i=1}^k \lambda_i^{-1}$ .
- $\Phi_p$ -optimality: minimize  $\sum_{i=1}^k \lambda_i^{-p}$  with 0 .
- E-optimality (eigenvalue): maximize  $\lambda_k$  (the minimum eigenvalue).

# Type-1 optimality criteria

• M: non-negative definite symmetric matrix of rank k with eigenvalues  $\lambda_1, \ldots, \lambda_k$ .

# Definition (Type 1 optimality criteria [Cheng, 1978]<sup>9</sup>)

A type 1 criterion is of the form  $\Phi_f(\mathbf{M}) = \sum_{i=1}^k f(\lambda_i)$ , where  $f: \mathbb{R} \to [0, \infty)$  is continuously differentiable in  $(0, \infty)$  with f' < 0, f'' > 0, and f''' < 0, and  $\lim_{x \to 0^+} f(x) = f(0) = \infty$ .

In particular, the *D*-optimality criterion is of type 1 for  $f(\lambda) = -\log \lambda$ .

- $\mathcal{A}$ : the set of all  $k \times n$   $\{0,1\}$  circulant arrays.
- $\mathcal{M}_{\mathcal{A}} = \{ \mathbf{M}(\mathbf{A}) : \mathbf{A} \in \mathcal{A} \}.$

#### Definition (Optimality for CAOAs)

If  $\mathbf{M} \in \mathcal{M}_{\mathcal{A}}$  (resp.  $\mathbf{A} \in \mathcal{A}$  with  $\mathbf{M} = \mathcal{M}_{\mathcal{A}}$ ) minimizes  $\Phi_f(\mathbf{M})$  in the class  $\mathcal{M}_{\mathcal{A}}$  for all f, then  $\mathbf{M}$  (resp.  $\mathbf{A} \in \mathcal{A}$ ) is optimal over  $\mathcal{M}_{\mathcal{A}}$  (resp.  $\mathcal{A}$ ) w.r.t. all type 1 criteria.

盧 暁南 (Xiao-Nan LU) Advanced Applied Math II Aug. 31, 2021 Kobe University

34 / 48

<sup>&</sup>lt;sup>9</sup>C. S. Cheng, Optimality of certain asymmetrical experimental designs, Ann. Stat., 6: 1239–1261 (1978).

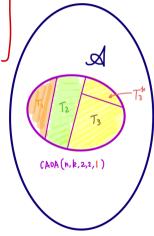
# Three types of CAOAs (Revisit)

- $n \equiv 2 \pmod{4}$  and  $k \ge 2$ .
- **A**: CAOA(n, k, 2, 2, 1)
- $\mathcal{A}$ : the set of  $k \times n$   $\{0,1\}$ -circulant arrays.

# h -2 2 -2 2 -2

# Definition ( $T_1$ -, $T_2$ -, $T_3$ -, $T_3^*$ -CAOA)

- **1** A is a  $T_1$ -CAOA if  $\mathbf{M}(\mathbf{A}) = (n-2)\mathbf{I}_k + 2\mathbf{J}_k$ , optimal (by [Cheng, et al., 2017]<sup>10</sup>)
- **2** A is a  $T_2$ -CAOA if  $\mathbf{M}(\mathbf{A}) = (n+2)\mathbf{I}_k 2\mathbf{J}_k$ ,
- **3 A** is a  $T_3$ -CAOA if **A** is neither  $T_1$  nor  $T_2$ -CAOA. In particular, if  $\mathbf{M}(\mathbf{A}) = (n-2)\mathbf{I}_k + 2\mathbf{L}_k$  with  $\mathbf{L}_k = (\ell_{ij})$  where  $\ell_{ij} = (-1)^{i+j}$ , then **A** is a  $T_3^*$ -CAOA. optimal [L.]



<sup>10</sup>C. S. Cheng, M. H. Kao, F. K. H. Phoa. Optimal and efficient designs for functional brain imaging experiments. J Statist. Plann. Inference 181: 71–80 (2017).

盧 暁南 (Xiao-Nan LU)

# A new type of optimal CAOAs

#### Theorem (L. et. al, 2021)

 $T_3^*$ -CAOA **A** is optimal over  $\mathcal{A}$  w.r.t. any type 1 criterion.

Proof (sketch):  $T_3^*$ -CAOA(n, k, 2, 2, 1) has the same eigenvalues with a  $T_1$ -CAOA(n, k, 2, 2, 1).

Actually, we proved a stronger theorem. 11

#### Theorem (L. et. al, 2021)

If there exists a  $T_1$ - or a  $T_3^*$ -CAOA(n,k,2,2,1), then, with respect to any type 1 criterion, any optimal array in  $\mathcal A$  is either a  $T_1$ - or a  $T_3^*$ -CAOA(n,k,2,2,1).

<sup>&</sup>lt;sup>11</sup>X.-N. Lu, M. Mishima, N. Miyamoto, M. Jimbo. Optimal and efficient designs for fMRI experiments via two-level circulant almost orthogonal arrays. J Statist. Plann. Inference, 213: 33-49, (2021).

### An example of $T_3^*$ -CAOA

- n = 14, k = 6.
- Generating vector (the first row of a CAOA): 11101100001010

$$\mathbf{M} = \begin{bmatrix} 14 & -2 & 2 & -2 & 2 & -2 \\ -2 & 14 & -2 & 2 & -2 & 2 \\ 2 & -2 & 14 & -2 & 2 & -2 \\ -2 & 2 & -2 & 14 & -2 & 2 \\ 2 & -2 & 2 & -2 & 14 & -2 \\ -2 & 2 & -2 & 2 & -2 & 14 \end{bmatrix}$$

• Eigenvalues of M: (24, 12, 12, 12, 12, 12)

#### Table of $T_3^*$ -CAOAs

#### Example $(T_3^*\text{-CAOA}(n, k_3^*, 2, 2, 1) \text{ (optimal)})$

$\overline{n}$	$k_3^*$	$(k_1)$	Generating vector
10	<u>5</u>	<u>(3)</u>	1101000101
14	<u>6</u>	$(\underline{4})$	11101100001010
18	<u>6</u>	$(\underline{6})$	110101110100001001
22	<u>8</u>	$(\underline{7})$	0010100100011110111010
26	<u>13</u>	$(\underline{9})$	110101000001100101011111100
30	$\underline{14}$	$(\underline{10})$	1001111111001101010100000110010
34	<u>13</u>	$(\underline{11})$	0011000000011110011101101101010101
38	14	(13)	11010100000111000100010101101100111110
42	16	(13)	11011010111011110010101000001011001100
46	17	(14)	1011001001011110000100001001110100011101111
_50	18	(15)	0110101010100000110001100100011010011111

<sup>\*</sup> The best known k for  $T_1$ -CAOAs are also listed. The underlined values are best possible (cannot be larger).

#### Outline

- ① Binary sequences with optimal autocorrelation and cyclic designs
- 2 Statistical designs for fMRI experiments and cyclic almost orthogonal arrays (CAOA)
- 3 CAOAs, optimal sequences, and ADSs



### How large k can be? (1/2)

#### Proposition (Upper bound for k)

- **1** For  $n \geq 6$ , any of  $T_1$ -,  $T_2$  and  $T_3^*$ -CAOA(n, k, 2, 2, 1) satisfies  $k \leq n/2$ .
- 2 For  $n \geq 10$ , any  $T_1$ -CAOA(n, k, 2, 2, 1) satisfies  $k \leq n/2 2$ .

#### Problem

For which kind of  $T_3$ -CAOA(n, k, 2, 2, 1), k = n - 1 may hold?

### How large k can be? (2/2)

Example 
$$(T_3^*\text{-CAOA}(n=10,k=5,2,t=2,b=1) \text{ Revisit})$$

$$\mathbf{A} = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

## How large k can be? (2/2)

#### Example (Information matrix of $T_3^*$ -CAOA(n = 10, k = 5, 2, t = 2, b = 1))

$$\mathbf{M}(\mathbf{A}) = \begin{bmatrix} 10 & -2 & 2 & -2 & 2 \\ -2 & 10 & -2 & 2 & -2 \\ 2 & -2 & 10 & -2 & 2 \\ -2 & 2 & -2 & 10 & -2 \\ 2 & -2 & 2 & -2 & 10 \end{bmatrix}.$$

### How large k can be? (2/2)

Example (Forcing 
$$k=9$$
 for a  $T_3^*$ -CAOA $(n=10,k=5,2,t=2,b=1)...)$ 

$$\mathbf{M}(\mathbf{A}) = \begin{bmatrix} 10 & -2 & 2 & -2 & 2 & -10 & 2 & -2 & 2 \\ -2 & 10 & -2 & 2 & -2 & 2 & -10 & 2 & -2 \\ 2 & -2 & 10 & -2 & 2 & -2 & 2 & -10 & 2 \\ -2 & 2 & -2 & 10 & -2 & 2 & -2 & 2 & -10 \\ \vdots & \vdots \end{bmatrix}.$$

#### $T_3$ -CAOAs and sequences

#### Theorem (Relationship between $T_3$ -CAOAs and sequences)

For  $n \equiv 2 \pmod{4}$ , the following are equivalent:

- 1 There exists a perfect binary sequence of length n consisting of equal numbers of 0 and 1 (called balanced);
- 2 A  $T_3$ -CAOA(n, n-1, 2, 2, 1) (not necessarily  $T_3^*$ ) exits;
- 3 A  $T_3$ -CAOA(n, k, 2, 2, 1) (not necessarily  $T_3^*$ ) exits for any  $n/2 < k \le n-1$ .

## Binary balanced optimal sequences and almost difference sets (revisit)

- For  $\mathbf{s} \in \{0,1\}^n$ , regard the indices as in  $\mathbb{Z}_n = \{0,1,\ldots,n-1\}$ .
- The set of indices of 1's in s is the support of s, denoted by supp(s).
- For an optimal s with  $n \equiv 2 \pmod{4}$ ,  $\operatorname{supp}(s)$  is an almost difference set in  $\mathbb{Z}_n$ .

#### Proposition

A  $T_3$ -CAOA(n, k, 2, 2, 1) with generating vector  $\mathbf{s} \iff$ 

An optimal balanced binary sequence  $\mathbf{s} \iff$ 

 $D:=\operatorname{supp}(\mathbf{s})$  is an  $(n,\frac{n}{2},\frac{n-2}{4},\frac{3n-2}{4})$  ADS in  $\mathbb{Z}_n$ 

## Known constructions for sequences (revisit)

Using known sequence constructions and computer search, we have:

#### Theorem

There exits a  $T_3$ -CAOA(n, n-1, 2, 2, 1) for the following n:

- **1** (From SLCE seq.) n = q 1, where  $q \equiv 3 \pmod{4}$  is a power of a prime;
- 2 (From DHM seq.) n=2p, where  $p\equiv 5\pmod 8$  is a prime such that p-1 or p-4 is a perfect square.
- $n \in \{34, 38, 50\}.$

## Comparison of D-efficiency(%) between $T_3$ - and $T_2$ -CAOAs

		k =	= n/2	k = n - 1		k = 9		
$\frac{n}{}$		$T_3$	$(T_2)$	$T_3$	$(T_2)$	$T_3$	$(T_2)$	
6	S	92.83	(92.83)	84.41	(84.41)	NA	NA	
10	S	97.67	(89.13)	82.74	(69.44)	82.74	(69.44)	
10 -	D	97.67	(89.13)	82.74	(69.44)	82.74	(69.44)	
18	S	97.01	(89.01)	85.28	(55.47)	97.01	(89.01)	
22	S	97.14	(89.49)	86.38	(51.24)	98.05	(95.79)	
26	S	98.16	(90.00)	87.37	(47.91)	99.08	(97.78)	
20	D	98.16	(90.00)	87.37	(47.91)	99.08	(97.78)	
30	S	98.02	(90.50)	88.17	(45.18)	99.43	(98.66)	
34	РС	99.05	(90.95)	91.26	(42.89)	99.79	(99.12)	
34		98.61	(90.95)	90.09	(42.89)	99.59	(99.12)	
38	PC	98.39	(91.37)	91.79	(40.93)	99.59	(99.39)	
42	S	98.67	(91.75)	90.08	(39.23)	99.65	(99.56)	
46	S	98.76	(92.10)	90.57	(37.73)	99.87	(99.67)	
50	PC	98.88	(92.42)	92.17	(36.39)	99.87	(99.75)	

# Enumerating $(n, \frac{n}{2}, \frac{n-2}{4}, \frac{3n-2}{4})$ ADS

#### **Problem**

For given  $n \equiv 2 \pmod{4}$ , how many different are there?

By further characterizing optimal balanced sequences and employing SUGAR<sup>12</sup>, a SAT-based constraint solver, a complete search of all optimal balanced sequences of length n=2u with  $u\in\{3,5,\ldots,23\}$  was carried out.

Table: The numbers of equivalence classes of optimal balanced sequences of length n

n=2u	6	10	14	18	22	26	30	34	38	42	46
# eq. classes	1	1	0	8	12	24	30	4	4	16	8
Known constr.	S	S,D	-	S	S	S,D	S	-	-	S	S

<sup>12</sup>https://cspsat.gitlab.io/sugar/

## Updated D-efficiency (%) of $T_3$ -CAOA(n, n-1, 2, 2, 1)

$\overline{n}$		$T_3$	best $T_3$
6	S	84.41	-
10	S	82.74	-
10	D	82.74	-
18	S	85.28	-
22	S	86.38	86.90
26	S	87.37	89.22
20	D	87.37	09.22
30	S	88.17	90.97
34	PC	91.26	
94	1	90.09	_
38	PC	91.79	91.89
42	S	90.08	92.58
46	S	90.57	92.51

## Homework assignments (レポート課題) for 5th day

#### Exercise 1

Construct an SLCE sequence of length n=18.

Hint: take q = 19.

#### Exercise 2

Find all the integers  $100 \le n \le 200$  such that there exists an SLCE sequence or a DHM sequence of length n.

- You are encouraged to use computer programs.
- Deadline: 6th Sept., 23:59:59