# Optimizing the Frobenius norm under structural constraints.

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#### Abstract

TODO: Rewrite this to be more general The approximation of a general matrix  $\mathbf{M}$  by a circulant matrix  $\mathbf{C}$  is explored. Using the discrete Fourier transform matrix  $\mathbf{F}$ , the circulant with eigenvalues given by the diagonals of  $\mathbf{FMF}^*$  is shown to be equivalent to the nearest circulant in the Frobenius norm,  $\mathbf{C}_M$ . An intuitive interpretation of this matrix in terms of means and variances of its values is presented.

### 1 Introduction

#### TODO: Preamble, justification

Circulant matrices are matrices of the form

$$\mathbf{C} = \begin{bmatrix} c_0 & c_1 & c_2 & \dots & c_{n-2} & c_{n-1} \\ c_{n-1} & c_0 & c_1 & \dots & c_{n-3} & c_{n-2} \\ c_{n-2} & c_{n-1} & c_0 & \dots & c_{n-4} & c_{n-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ c_2 & c_3 & c_4 & \dots & c_0 & c_1 \\ c_1 & c_2 & c_3 & \dots & c_{n-1} & c_0 \end{bmatrix}$$
(1)

with  $c_0, c_1, \ldots, c_{n-1} \in \mathbb{C}$ . They see widespread use in signal processing, computation, and physical modelling as matrices with known eigensystems [1, 2]. For **C** as in Equation 5, the ordered eigenvalues for  $k = 0, 1, \ldots, n-1$  are given by

$$\lambda_k = c_0 + \sum_{l=1}^{n-1} c_l \omega^{lk} \tag{2}$$

and the corresponding  $k^{\text{th}}$  eigenvector is given by

$$\mathbf{x}_{k} = \begin{bmatrix} 1 \\ \omega^{k} \\ \omega^{2k} \\ \vdots \\ \omega^{(M-1)k} \end{bmatrix}$$

$$(3)$$

where  $\omega = \exp(\frac{2\pi i}{n})$  is the complex  $n^{\text{th}}$  root of unity and  $i = \sqrt{-1}$ .

Much of the utility of circulant matrices arises from this eigensystem. The  $n \times n$  matrix of eigenvectors of  $\mathbf{C}$  scaled to be unitary,

$$\mathbf{F} = \frac{1}{\sqrt{n}} [\mathbf{x}_0 | \mathbf{x}_1 | \mathbf{x}_2 | \dots | \mathbf{x}_{n-1}] = \mathbf{F}^\mathsf{T}, \tag{4}$$

is simply the discrete Fourier transform (DFT). Circulant matrices therefore have a deep relationship with real and complex analysis [3].

Suppose we would like to take advantage of this depth of theory and practice to approximate the  $n \times n$  matrix

$$\mathbf{M} = \begin{bmatrix} m_{11} & m_{12} & \dots & m_{1n} \\ m_{21} & m_{22} & \dots & m_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ m_{n1} & m_{n2} & \dots & m_{nn} \end{bmatrix}$$
 (5)

by some circulant matrix. This note outlines some results.

# 2 Approximating M using F

Consider the simple approximation algorithm:

- 1. construct the diagonal matrix **D** where  $d_{jj} = (\mathbf{F}\mathbf{M}\mathbf{F}^*)_{jj}$  and  $\mathbf{F}^*$  is the complex conjugate of  $\mathbf{F}$ ,
- 2. compute  $\mathbf{C}_D = \mathbf{F}^* \mathbf{D} \mathbf{F}$ .

As **D** is diagonal and **F** is the matrix of eigenvectors for any circulant matrix,  $\mathbf{C}_D$  is a circulant matrix with eigenvalues given by  $d_{jj}$ . To determine the elements  $(\mathbf{C}_D)_{ij}$  in terms of  $\omega$ ,  $\mathbf{x}$ , and  $\mathbf{M}$ , first note

$$d_{jj} = \frac{1}{n} \sum_{k=1}^{n} \sum_{l=1}^{n} \omega^{(k-l)(j-1)} m_{lk}.$$
 (6)

Analogously, taking  $F^*DF$  gives an i, j element

$$(\mathbf{C}_{D})_{ij} = \mathbf{F}^{*}\mathbf{D}\mathbf{F}$$

$$= \frac{1}{n^{2}} \sum_{l=1}^{n} \sum_{k=1}^{n} m_{lk} \mathbf{x}_{k-l}^{*} \mathbf{x}_{i-j}$$

$$= \frac{1}{n} \sum_{l=1}^{n} \sum_{k=1}^{n} m_{lk} \delta_{(i-j) \bmod n, (k-l) \bmod n}$$

$$(7)$$

where  $\delta_{ij}$  is the Kronecker delta defined by

$$\delta_{ij} = \begin{cases} 0 \text{ if } i \neq j \\ 1 \text{ if } i = j. \end{cases}$$
 (8)

Equation 7 indicates that  $C_D$  is generated by replacing the values of M along each circulant diagonal by the corresponding diagonal mean. Expressed as in Equation 1,  $C_D$  is the circulant matrix with

$$c_k = \frac{1}{n} \sum_{\{i,j \mid (i-j) \bmod n = k\}} m_{ij} := \overline{m}_k \tag{9}$$

Remarkably, though this was not the original motivation,  $C_D$  is also optimal in the sense of [1]: it minimizes the Frobenius norm.

**Theorem 1** ( $\mathbf{C}_D$  is Frobenius optimal).  $\mathbf{C}_D$  minimizes  $||\mathbf{C} - \mathbf{M}||_F$  for circulant  $\mathbf{C}$ , where  $||\mathbf{A}||_F$  is the Frobenius norm of  $\mathbf{A}$ .

*Proof.* We can write  $||\mathbf{C} - \mathbf{M}||_F$  as

$$\sqrt{\operatorname{trace}\left(\left(\mathbf{C} - \mathbf{M}\right)^{*}(\mathbf{C} - \mathbf{M})\right)}.$$
(10)

Any C which minimizes Equation 10 will also minimize  $||\mathbf{C} - \mathbf{M}||_F^2$ . Therefore we seek to minimize

$$\operatorname{trace}\left((\mathbf{C} - \mathbf{M})^*(\mathbf{C} - \mathbf{M})\right) = \operatorname{trace}\mathbf{M}^*\mathbf{M} - \operatorname{trace}\mathbf{M}^*\mathbf{C} - \operatorname{trace}\mathbf{C}^*\mathbf{M} + \operatorname{trace}\mathbf{C}^*\mathbf{C}.$$
(11)

 $\mathbf{M}^*\mathbf{M}$  is constant in  $\mathbf{C}$ , so this term can be ignored in the optimization. The latter three terms can be considered individually to express them as terms of the  $c_i$ . trace  $\mathbf{C}^*\mathbf{C}$  is the simplest, as

trace 
$$\mathbf{C}^*\mathbf{C} = n\sum_{i=0}^{n-1} c_i^* c_i$$
. (12)

The negative terms can be expressed

trace 
$$\mathbf{M}^* \mathbf{C} = \sum_{i=1}^n \sum_{j=1}^n m_{ji}^* c_{(i-j) \bmod n}$$
  

$$= \sum_{i=0}^{n-1} c_i \left( \sum_{j=1}^{n-i} m_{j,j+i}^* + \sum_{j=1}^i m_{n-i+j,j}^* \right)$$

$$= n \sum_{i=0}^{n-1} c_i \overline{m}_i^*$$
(13)

and

trace 
$$\mathbf{C}^* \mathbf{M} = n \sum_{i=0}^{n-1} c_i^* \overline{m}_i.$$
 (14)

So we seek to minimize

$$F(\mathbf{c}) = n \sum_{i=0}^{n-1} c_i^* c_i - n \sum_{i=0}^{n-1} c_i^* \overline{m}_i - n \sum_{i=0}^{n-1} c_i \overline{m}_i^*$$
$$= n \left( \langle \mathbf{c}, \mathbf{c} \rangle - \langle \overline{\mathbf{m}}, \mathbf{c} \rangle - \langle \mathbf{c}, \overline{\mathbf{m}} \rangle \right)$$
(15)

where  $\langle \mathbf{x}, \mathbf{y} \rangle \geq 0$  is the Hermitian inner product of  $\mathbf{x}, \mathbf{y} \in \mathbb{C}$ ,  $\mathbf{c} = (c_0, c_1, \dots, c_{n-1})^\mathsf{T}$  is the first row of  $\mathbf{C}$ , and  $\overline{\mathbf{m}} = (\overline{m}_0, \overline{m}_1, \dots, \overline{m}_{n-1})^\mathsf{T}$  is the vector of diagonal means of  $\mathbf{M}$ .

 $\langle \overline{\mathbf{m}}, \mathbf{c} \rangle$  and  $\langle \mathbf{c}, \overline{\mathbf{m}} \rangle$  are maximized when  $\mathbf{c} = t\overline{\mathbf{m}}$  for  $t \in \mathbb{R}$  and  $\langle \mathbf{c}, \mathbf{c} \rangle$  simply gives the squared magnitude of  $\mathbf{c}$ . Therefore, the minimizer of Equation 15 must be  $\mathbf{c} = t\overline{\mathbf{m}}$  for some  $t \in \mathbb{R}$ . Substituting this into Equation 15:

$$F(t\overline{\mathbf{m}}) = n\left(t^2\langle \overline{\mathbf{m}}, \overline{\mathbf{m}}\rangle - t\langle \overline{\mathbf{m}}, \overline{\mathbf{m}}\rangle - t\langle \overline{\mathbf{m}}, \overline{\mathbf{m}}\rangle\right)$$
$$= n||\overline{\mathbf{m}}||^2(t^2 - 2t), \tag{16}$$

which has a minimum of  $-n||\overline{\mathbf{m}}||^2$  when t=1. Therefore,  $\mathbf{c}=\overline{\mathbf{m}}$  minimizes  $F(\mathbf{c})$  and so the optimal circulant matrix  $\mathbf{C}$  to approximate  $\mathbf{M}$  in the Frobenius norm satisfies Equation 9.

Recognizing that the value of the squared Frobenius norm is

$$||\mathbf{C} - \mathbf{M}||_F^2 = \operatorname{trace} \mathbf{M}^* \mathbf{M} + F(\mathbf{c}) = \sum_{i=1}^n \sum_{j=1}^n ||m_{ij}||^2 + F(\mathbf{c}),$$

substituting  $\mathbf{c} = \overline{\mathbf{m}}$  gives a minimum

$$||\mathbf{C}_{D} - \mathbf{M}||_{F}^{2} = \sum_{i=1}^{n} \sum_{j=1}^{n} ||m_{ij}||^{2} - n||\overline{\mathbf{m}}||^{2}$$

$$= n \left( \sum_{k=0}^{n-1} \sum_{\{1 \le i, j \le n | (i-j) \bmod n = k\}} \frac{||m_{ij}||^{2}}{n} - \sum_{k=0}^{n-1} ||\overline{m}_{k}||^{2} \right)$$

$$= n \sum_{k=0}^{n-1} \sigma_{k}^{2}$$
(17)

where  $\sigma_k^2$  is the variance of values along the  $k^{\text{th}}$  diagonal of  $\mathbf{M}$ . Therefore the value of the Frobenius norm  $||\mathbf{C}_D - \mathbf{M}||_F$  is given by the total standard deviation of the values of  $\mathbf{M}$  from their respective circulant diagonals!

# 3 Other structured matrices

The proof provided for Theorem 1 does not apply to circulant matrices alone, as the grouping of terms in the sums is arbitrary. Suppose we have some structured matrix  $\mathbf{A}$  with entries  $a_{ij}$  which have constant values following a regular pattern in i and j. That is,

$$a_{ij} = a_{f(i,j)} \tag{18}$$

where  $f: \{0, 1, ..., n-1\}^2 \mapsto \{0, 1, 2, ..., K\}$  indicates the membership of the index pair i, j to a constant index set indexed by k. Define

$$\mathcal{A}_k = \{(i,j)|f(i,j) = k\}$$

with cardinality  $|A_k| = n_k > 0$ , then Equations 13 and 14 can be generalized to

trace 
$$\mathbf{M}^* \mathbf{A} = \sum_{i=1}^n \sum_{j=1}^n m_{ji}^* a_{ij}$$

$$= \sum_{k=0}^K a_k \sum_{\mathcal{A}_k} m_{ji}^*$$
(19)

and

trace 
$$\mathbf{A}^* \mathbf{M} = \sum_{k=0}^K a_k^* \sum_{\mathcal{A}_k} m_{ji},$$
 (20)

respectively. Define the mean of entries in  ${\bf M}$  for the  $k^{\rm th}$  index set,

$$\overline{m}_k := \frac{1}{n_k} \sum_{A_k} m_{ij}; \tag{21}$$

the vector of all such means,

$$\overline{\mathbf{m}} = (\overline{m}_0, \overline{m}_1, \dots, \overline{m}_K)^{\mathsf{T}} \tag{22}$$

the vector of unique  $a_k$ ,

$$\mathbf{a} = (a_0, a_1, \dots, a_K)^\mathsf{T}; \tag{23}$$

and the diagonal matrix of  $n_k$ ,

$$\mathbf{N} = \operatorname{diag}(n_0, n_1, \dots, n_K) \tag{24}$$

Then Equation 15 becomes

$$F(\mathbf{a}) = \mathbf{a}^* \mathbf{N} \mathbf{a} - \overline{\mathbf{m}}^* \mathbf{N} \mathbf{a} - \mathbf{a}^* \mathbf{N} \overline{\mathbf{m}}$$
 (25)

$$= (\mathbf{a} - \overline{\mathbf{m}})^* \mathbf{N} (\mathbf{a} - \overline{\mathbf{m}}) - \overline{\mathbf{m}}^* \mathbf{N} \overline{\mathbf{m}}. \tag{26}$$

As  $n_k > 0$  for all k = 0, 1, ..., K, **N** is positive definite, and so the quadratic form  $\mathbf{x}^* \mathbf{N} \mathbf{x}$  has a minimum of zero when  $\mathbf{x} = \mathbf{0}$ . Therefore  $F(\mathbf{a})$  is minimized for  $\mathbf{a} = \overline{\mathbf{m}}$  and has a minimum of

$$F(\overline{\mathbf{m}}) = -\overline{\mathbf{m}}^* \mathbf{N} \overline{\mathbf{m}} = -\sum_{k=0}^K n_k ||\overline{m}_k||^2.$$
 (27)

Letting  $\mathbf{A}_{M}$  be the Frobenius-optimal structural matrix  $\mathbf{A}$  to approximate  $\mathbf{M}$ , this gives

$$||\mathbf{A}_{M} - \mathbf{M}||_{F}^{2} = \sum_{k=0}^{K} \sum_{\mathcal{A}_{k}} ||m_{ij}||^{2} - \sum_{k=0}^{K} n_{k} ||\overline{m}_{k}||^{2}$$

$$= \sum_{k=0}^{K} n_{k} \left( \sum_{\mathcal{A}_{k}} \frac{||m_{ij}||^{2}}{n_{k}} - ||\overline{m}_{k}||^{2} \right)$$

$$= \sum_{k=0}^{K} n_{k} \sigma_{k}^{2}$$
(28)

where

$$\sigma_k^2 = \frac{1}{n_k} \sum_{A_k} \left( m_{ij} - \overline{m}_k \right)^2$$

is the variance of the  $m_{ij}$  for the index set  $\mathcal{A}_k$ .

Toeplitz matrices are matrices of the form

$$\mathbf{T} = \begin{bmatrix} t_0 & t_1 & t_2 & \dots & t_{n-2} & t_{n-1} \\ t_{-1} & t_0 & t_1 & \dots & t_{n-3} & t_{n-2} \\ t_{-2} & t_{-1} & t_0 & \dots & t_{n-4} & t_{n-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ t_{2-n} & t_{3-n} & t_{4-n} & \dots & t_0 & t_1 \\ t_{1-n} & t_{2-n} & t_{3-n} & \dots & t_{-1} & t_0 \end{bmatrix}$$
(30)

Hankel matrices are matrices of the form

$$\mathbf{H} = \begin{bmatrix} h_0 & h_1 & h_2 & \dots & h_{n-2} & h_{n-1} \\ h_1 & h_2 & h_3 & \dots & h_{n-1} & h_n \\ h_2 & h_3 & h_4 & \dots & h_n & h_{n+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ h_{n-2} & h_{n-1} & h_n & \dots & h_{2n-4} & h_{2n-3} \\ h_{n-1} & h_n & h_{n+1} & \dots & h_{2n-3} & h_{2n-2} \end{bmatrix}$$
(31)

# References

[1] Tony F Chan. An optimal circulant preconditioner for toeplitz systems. SIAM Journal on Scientific and Statistical Computing, 9(4):766–771, 1988.

- [2] Robert M Gray. Toeplitz and circulant matrices: A review. now Publishers Inc., 2006.
- [3] Ulf Grenander and Gabor Szegö. *Toeplitz forms and their applications*. University of California Press, 1958.