For any 
$$X \in \mathbb{R}^{n \times n}$$
 and  $\epsilon \in (0,1]$ . Then, with  $r = \lceil 72 \log(2n+1)/\epsilon^2 \rceil$ , we have 
$$\inf_{\operatorname{rank}(Y) \leq r} \|X - Y\|_{\max} \leq \epsilon \|X\|_2$$

 $\begin{bmatrix} 1 & 2 & 3 & 4 & 5 \\ 5 & 1 & 2 & 3 & 4 \\ 4 & 5 & 1 & 2 & 3 \\ 3 & 4 & 5 & 1 & 2 \\ 2 & 3 & 4 & 5 & 1 \end{bmatrix}$ 

$$N$$
 charges:  $\{q_i, r_i\}_{i=1}^N$ 

Potential: 
$$\phi_i = \sum_{j \neq i} \frac{q_j}{\|r_i - r_j\|}$$
 for  $i \in \{1, 2, \dots, N\}$ 

Note that we have  $\phi = Aq$ ,  $\phi$  is the set of potentials, q is the set of charges and  $A_{ij} = \frac{1}{\|r_i - r_j\|}$  for  $i \neq j$ 

Matrix-vector product: Given q, compute  $\phi$ . Cost is  $\mathcal{O}(N^2)$ 

Solve linear system: Given  $\phi$ , compute q. Cost is  $\mathcal{O}(N^3)$ 

Can we reduce the above computational complexity to say  $\mathcal{O}(N)$ ?

Let's look at a slightly easier problem

$$N$$
 charges:  $\{q_i, r_i\}_{i=1}^N$ 

Potential: 
$$\phi_i = \sum_{j=1}^{N} \sin(k(r_i - r_j)) q_j$$
 for  $i \in \{1, 2, \dots, N\}$ 

Matrix-vector product: Aq, where  $A_{ij} = \sin(k(r_i - r_j))$  for  $i \neq j$ 

Computational cost is  $\mathcal{O}(N^2)$ 

Can we reduce the computational complexity?

Note that  $\sin (k(r_i - r_j)) = \sin (kr_i) \cos (kr_j) - \cos (kr_i) \sin (kr_j)$ 

$$\phi_i = \sum_{j=1}^N \sin(kr_i)\cos(kr_j) q_j - \sum_{j=1}^N \cos(kr_i)\sin(kr_j) q_j$$
for  $i \in \{1, 2, \dots, N\}$ 

$$\phi_i = \left(\sum_{j=1}^N \cos(kr_j) \, q_j\right) \sin(kr_i) - \left(\sum_{j=1}^N \sin(kr_j) \, q_j\right) \cos(kr_i)$$
for  $i \in \{1, 2, \dots, N\}$ 

Compute 
$$a = \sum_{j=1}^{N} \cos(kr_j) q_j$$
; Cost is  $\mathcal{O}(N)$ 

Compute 
$$b = \sum_{j=1}^{N} \sin(kr_j) q_j$$
; Cost is  $\mathcal{O}(N)$ 

$$\phi_i = a \sin(kr_i) - b \cos(kr_i)$$
 for  $i \in \{1, 2, \dots, N\}$ ; Cost is  $\mathcal{O}(N)$ 

Total cost is  $\mathcal{O}(N)$ 

## Wait... What happened?

How did we go from  $\mathcal{O}(N^2)$  to  $\mathcal{O}(N)$ ?

In matrix form, we rewrote the matrix A as

$$A = u_1 v_1^T - v_1 u_1^T$$

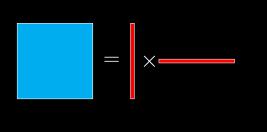
$$A = \begin{bmatrix} u_1 & -v_1 \end{bmatrix}_{N \times 2} \begin{bmatrix} v_1^T \\ u_1^T \end{bmatrix}_{2 \times N}$$

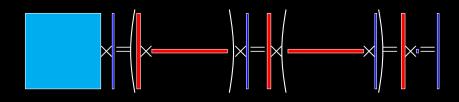
$$u_1 = \begin{bmatrix} \sin(kr_1) \\ \sin(kr_2) \\ \vdots \\ \sin(kr_N) \end{bmatrix}$$

$$v_1 = \begin{bmatrix} \cos(kr_1) \\ \cos(kr_2) \\ \vdots \\ \cos(kr_N) \end{bmatrix}$$

Hence,

$$Aq = u_1 \left( v_1^T q \right) - v_1 \left( u_1^T q \right)$$





Does the same idea work for  $1/\|r_i - r_j\|$  instead of  $\sin(k(r_i - r_j))$ ?

Unfortunately, not.

The "kernel" (Green's function) 1/r has a singularity at the origin.

Let's look at other kernel functions; For instance,  $\log(r)$ 

But what about away from the singularity?

Away from the singularity the matrix looks like low-rank (?)

Can this be proved?

Yes! The matrix is indeed low-rank in finite precision!

Away from the singularity, the kernel is smooth and a separable expansion of the kernel can be obtained

$$K(x,y) = \sum_{i,j=1}^{r} c_{ij}\phi_i(x)\psi_j(y) + \mathcal{O}(\epsilon)$$

where  $r = \mathcal{O}(\log(1/\epsilon))$  uniformly across the domain of x and y.

## An appropriate series (Taylor or Eigen-function) expansion of the kernel into separable expansions

We could also rely on polynomial interpolation to construct separable expansions

The rank r is independent of N

Fast Multipole Method - souped version of the previous mentioned

- Relies on hierarchically sub-dividing your domain
- ullet Identifying blocks to leverage low-rank matrix vector products Total computational complexity is  $\mathcal{O}(rN)$

Fast Multipole Method in Computational Physics

Matrices arising out of N-body problems have an even nicer structure