

APPM 4720/5720 — week 13:

The Potential Evaluation Map

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The potential evaluation map

In this lecture, we will look more carefully at the map that given a source distribution q in a (“source”) domain Ω_s evaluates the potential in a (“target”) domain Ω_t :

$$[Aq](\mathbf{x}) = \int_{\Omega_s} \phi(\mathbf{x} - \mathbf{y}) q(\mathbf{y}) dA(\mathbf{y}), \quad \mathbf{x} \in \Omega_t.$$

We will cover two cases in detail:

1. Laplace: $\phi(\mathbf{x}) = \log |\mathbf{x}|$.
2. Helmholtz: $\phi(\mathbf{x}) = H_0^{(1)}(\kappa|\mathbf{x}|)$.

The discussion will more generally apply to elasticity, Stokes, the equations of elasticity, time-harmonic Maxwell, etc.

Themes:

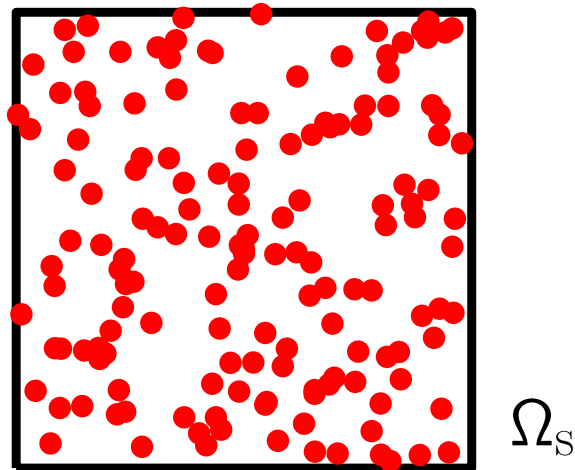
- The effective “rank of interaction”.
- Loss of information.
- Techniques for “compressing” the interaction.

Let us start with a Laplace problem (for me, it helps to think of it as electro-statics).

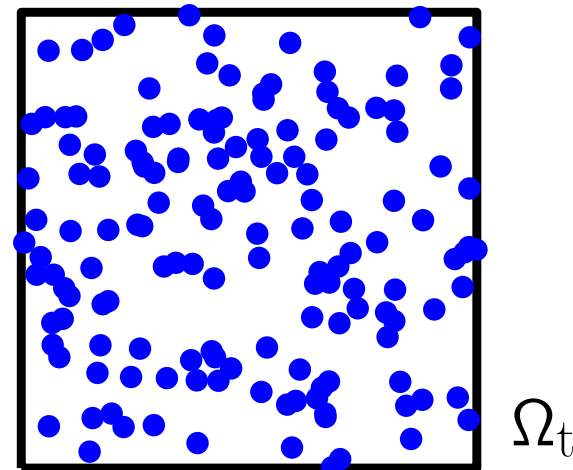
Suppose we are given two “well-separated” domains Ω_s and Ω_t .

There are m sources in Ω_s inducing n potentials in Ω_t .

Source locations $\{\mathbf{y}_j\}_{j=1}^n$



Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Let \mathbf{A} denote the $m \times n$ matrix with entries

$$\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|.$$

Given a vector $\mathbf{q} \in \mathbb{R}^n$ of source strengths, we seek a vector of potentials $\mathbf{f} \in \mathbb{R}^m$, where

$$\begin{array}{ccccc} \mathbf{f} & = & \mathbf{A} & \mathbf{q} & \\ m \times 1 & & m \times n & n \times 1 & \end{array}$$

Using direct evaluation, the cost is $O(mn)$.

A is the $m \times n$ matrix

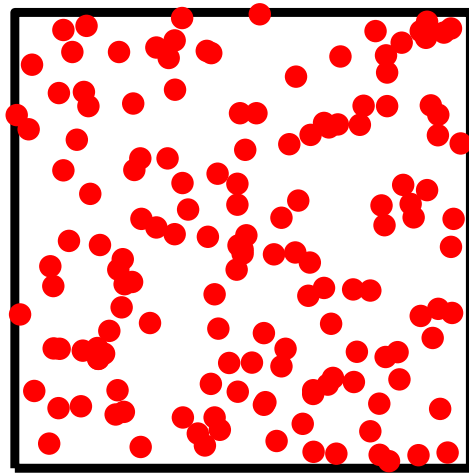
with entries

$$\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|.$$

We seek to evaluate

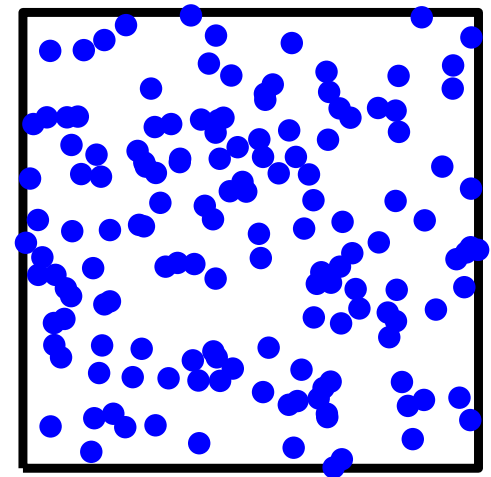
$$\mathbf{q} \mapsto \mathbf{f} = \mathbf{A}\mathbf{q}.$$

Source locations $\{\mathbf{y}_j\}_{j=1}^n$



Ω_s

Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Ω_t

\mathbf{A} is the $m \times n$ matrix

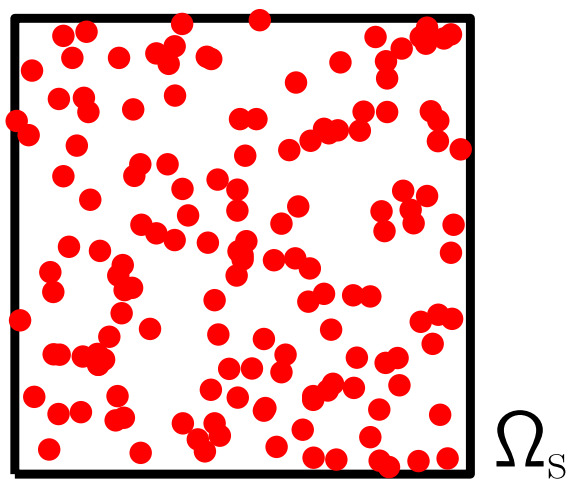
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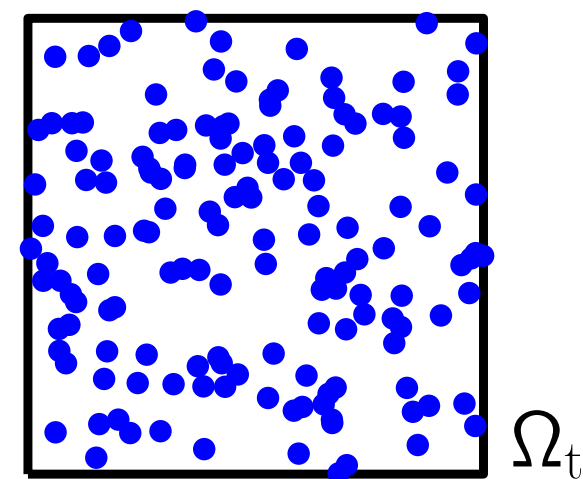
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Source locations $\{\mathbf{y}_j\}_{j=1}^n$



Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Multipole Expansion: We showed that we can separate variables in the kernel,

$$\log |\mathbf{x} - \mathbf{y}| = \sum_{p=0}^{\infty} B_p(\mathbf{x}) C_p(\mathbf{y}).$$

Using polar coordinates,

$$\mathbf{x} - \mathbf{c}_s = r e^{i\theta}, \quad \text{and} \quad \mathbf{y} - \mathbf{c}_s = r' e^{i\theta'},$$

the functions B_p and C_p can (for instance) be

$$\begin{aligned} B_0(\mathbf{x}) &= \log r, & C_0(\mathbf{y}) &= 1 \\ B_{2p-1}(\mathbf{x}) &= -\frac{\sin(p\theta)}{p r^p}, & C_{2p-1}(\mathbf{y}) &= (r')^p \sin(p\theta'), \\ B_{2p}(\mathbf{x}) &= -\frac{\cos(p\theta)}{p r^p}, & C_{2p}(\mathbf{y}) &= (r')^p \cos(p\theta'). \end{aligned}$$

Upon truncation, we have $\left| \log |\mathbf{x} - \mathbf{y}| - \sum_{p=0}^k B_p(\mathbf{x}) C_p(\mathbf{y}) \right| \lesssim (\sqrt{2}/3)^{k/2}$.

\mathbf{A} is the $m \times n$ matrix

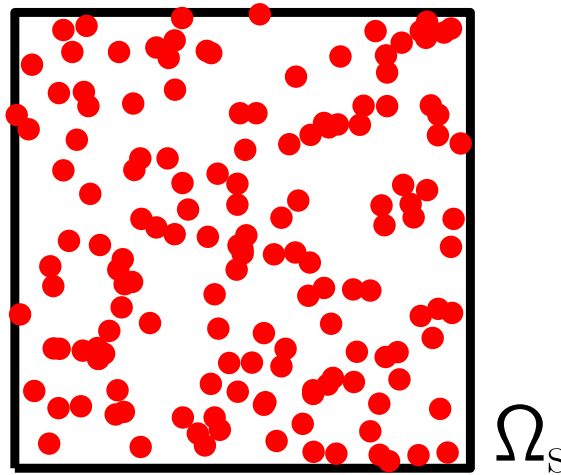
with entries

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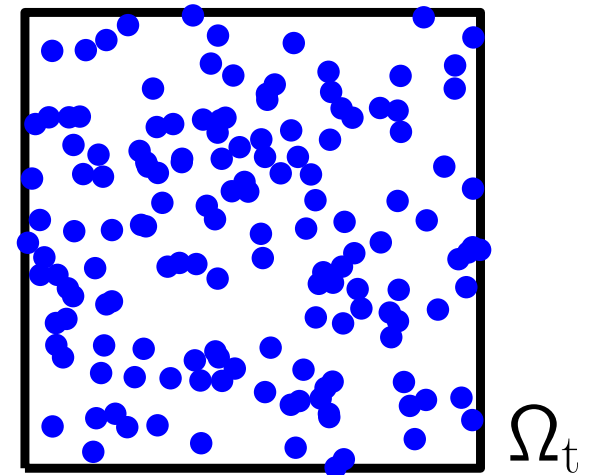
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Multipole Expansion: The precise form of the factors is not directly relevant for the discussion at hand, so to keep the notation uncluttered, let us simply write the approximation as

$$\log |\mathbf{x} - \mathbf{y}| \approx \sum_{p=1}^k B_p(\mathbf{x}) C_p(\mathbf{y}).$$

Note that we truncated the expansion after k terms, incurring an error $\approx (\sqrt{2}/3)^{k/2}$.

(We changed the summation index to start at 1, too.)

\mathbf{A} is the $m \times n$ matrix

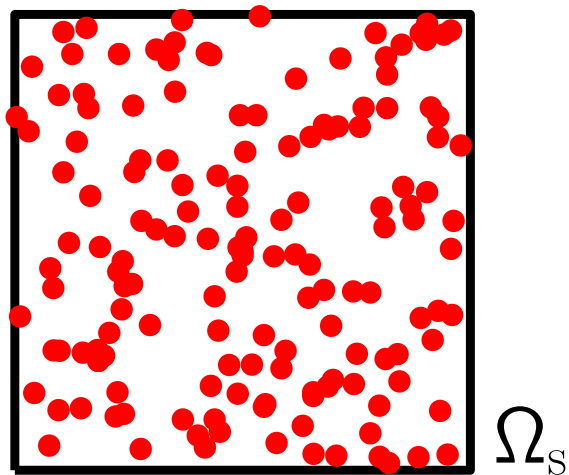
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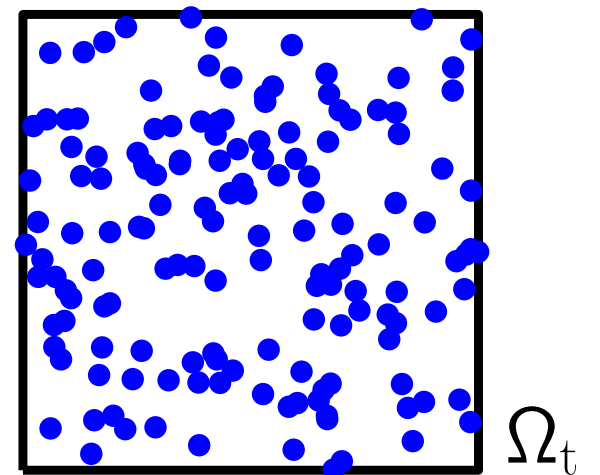
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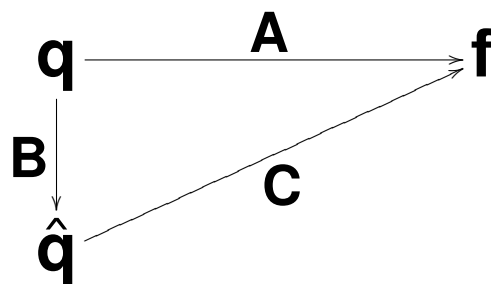
Multipole Expansion: Recall the k term multipole expansion:

$$(1) \quad \log |\mathbf{x} - \mathbf{y}| \approx \sum_{p=1}^k B_p(\mathbf{x}) C_p(\mathbf{y}).$$

An approximation (1) is called a *separation of variables*, and directly leads to a low-rank factorization

$$\begin{array}{ccccc} \mathbf{A} & \approx & \mathbf{B} & \mathbf{C} & \\ m \times n & & m \times k & k \times n & \end{array}$$

where \mathbf{B} has entries $\mathbf{B}(i, p) = B_p(\mathbf{x}_i)$ and \mathbf{C} has entries $\mathbf{C}(p, j) = C_p(\mathbf{y}_j)$.



Reduction in cost: *From mn flops to $2k(m + n)$ flops*, where $k \sim \log(1/\epsilon)$.

Suppose \mathbf{A} is a given $m \times n$ matrix.

Question: What is the theoretically “best” factorization of \mathbf{A} for any given ε ?

Answer: Consider the *singular value decomposition (SVD)* of \mathbf{A} :

$$\begin{array}{ccccccc} \mathbf{A} & \approx & \mathbf{U} & \mathbf{D} & \mathbf{V}^* & & \\ m \times n & & m \times r & r \times r & r \times n & & \end{array}$$

where $r = \min(m, n)$ and where

$\mathbf{U} = [\mathbf{u}_1 \ \mathbf{u}_2 \ \cdots \ \mathbf{u}_r]$ is a matrix holding the “left singular vectors” \mathbf{u}_j ,

$\mathbf{V} = [\mathbf{v}_1 \ \mathbf{v}_2 \ \cdots \ \mathbf{v}_r]$ is a matrix holding the “right singular vectors” \mathbf{v}_j ,

$\mathbf{D} = \text{diag}(\sigma_1, \sigma_2, \dots, \sigma_r)$ is a diagonal matrix holding the “singular values” σ_j .

Let $\|\cdot\|$ denote a matrix norm and let e_k denote the minimal error in a rank- k factorization

$$e_k = \min\{\|\mathbf{A} - \mathbf{A}_k\| : \mathbf{A}_k \text{ has rank } k\}.$$

Theorem (Eckart-Young): The minimal error is

$e_k = \sigma_{k+1}$, when the spectral norm is used

$e_k = \sqrt{\sigma_{k+1}^2 + \sigma_{k+2}^2 + \cdots + \sigma_r^2}$, when the Frobenius norm is used

and the minimal error is attained for the SVD truncated to the first k terms

$$e_k = \left\| \mathbf{A} - \sum_{j=1}^k \mathbf{u}_j \sigma_j \mathbf{v}_j^* \right\| = \left\| \mathbf{A} - \mathbf{U}_k \mathbf{D}_k \mathbf{V}_k^* \right\|.$$

\mathbf{A} is the $m \times n$ matrix

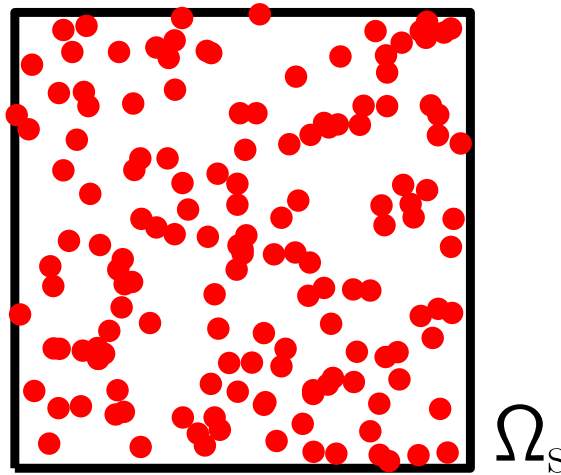
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$$\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|.$$

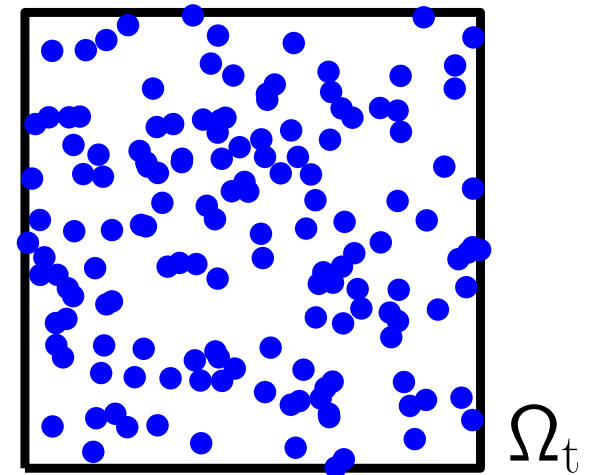
We seek to evaluate

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Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Optimal factorization — SVD: Compute the SVD of \mathbf{A} , and pick k such that $\sigma_{k+1} \leq \varepsilon$.

Set $\mathbf{B} = \mathbf{U}_k$ and $\mathbf{C} = \mathbf{D}_k \mathbf{V}_k^*$. Then

$$\begin{array}{ccccc} \mathbf{A} & \approx & \mathbf{B} & \mathbf{C} & \\ m \times n & & m \times k & k \times n & \end{array}$$

is the theoretically most economical factorization of \mathbf{A} .

However, the SVD is not quite ideal:

- All factors are determined numerically — expensive!
- The factors \mathbf{B} and \mathbf{C} depend on the precise geometry.



You have to custom-build all translation operators.

We will next describe a factorization that is almost optimal, and is also easy and economical to work with.

The Interpolative Decomposition (ID):

Let \mathbf{A} be an $m \times n$ matrix of (precise) rank k . Then \mathbf{A} admits a factorization

$$\mathbf{A} = \mathbf{A}^{(\text{skel})} \mathbf{V}^*,$$

$m \times n \quad m \times k \quad k \times n$

where

1. $\mathbf{A}^{(\text{skel})} = \mathbf{A}(:, \tilde{l})$ consists of k columns of \mathbf{A} .
2. \mathbf{V} contains a $k \times k$ identity matrix.
3. No entry of \mathbf{V} has magnitude greater than 1 (so \mathbf{V} is reasonably well-conditioned).

How do you construct an ID in practice?

- Computing an ID that satisfies (3) is (in general) very hard.
- If we relax condition (3) slightly, and require only that, say, $\max_{ij} |\mathbf{V}(i, j)| \leq 1.1$, then it can be done efficiently [1996, Gu & Eisenstat].
- In practice, simply performing Gram-Schmidt on the columns works great.
After k steps of column pivoted QR, we have

$$\mathbf{A}(:, l) = \mathbf{Q} [\mathbf{R}_{11} \quad \mathbf{R}_{12}] = \underbrace{\mathbf{Q}\mathbf{R}_{11}}_{=\mathbf{A}^{(\text{skel})}} \underbrace{[\mathbf{I} \quad \mathbf{R}_{11}^{-1}\mathbf{R}_{12}]}_{=\mathbf{V}^*}.$$

- If \mathbf{A} does not have exact rank k , *but its singular values decay rapidly*, then the ID resulting from Gram-Schmidt satisfies $\|\mathbf{A} - \mathbf{A}^{(\text{skel})}\mathbf{V}^*\| \approx \sigma_{k+1}$.

\mathbf{A} is the $m \times n$ matrix

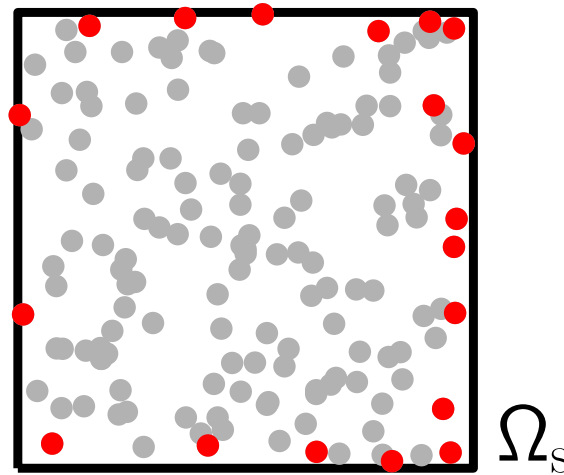
with entries

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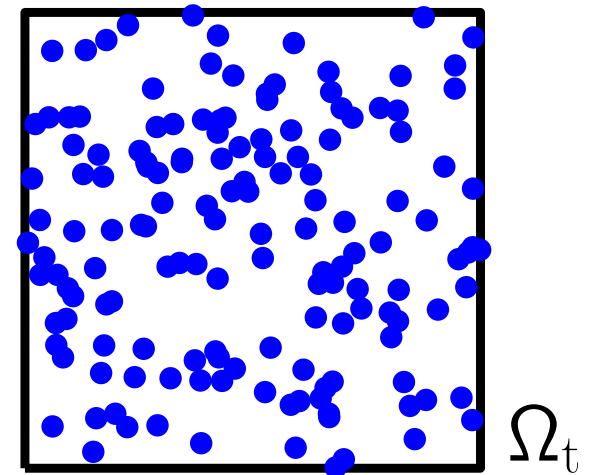
We seek to evaluate

$$\mathbf{q} \mapsto \mathbf{f} = \mathbf{A}\mathbf{q}.$$

Source locations $\{\mathbf{y}_j\}_{j=1}^n$



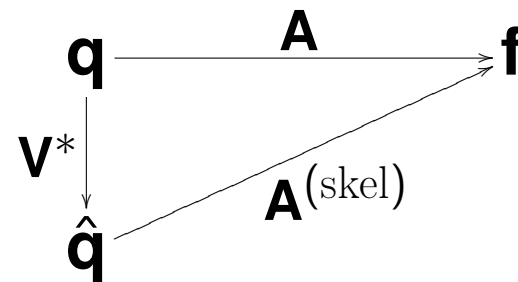
Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Interpolative decomposition (ID): Performing G-S on the columns of \mathbf{A} , we obtain

$$\begin{array}{ccc} \mathbf{A} & \approx & \mathbf{A}^{(\text{skel})} \mathbf{V}^* \\ m \times n & & m \times k \quad k \times n \end{array}$$

where $\mathbf{A}^{(\text{skel})} = \mathbf{A}(:, \tilde{l})$ consists of k columns of \mathbf{A} .



The nodes marked in red above are the nodes marked by the index vector \tilde{l} .

The interaction of Ω_s with the outside is through the original kernel function.

\mathbf{A} is the $m \times n$ matrix

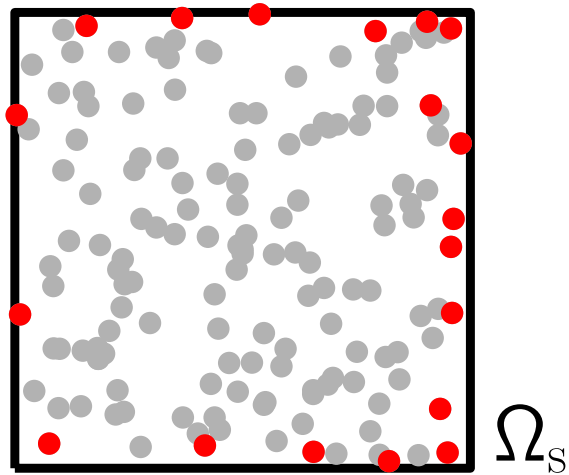
with entries

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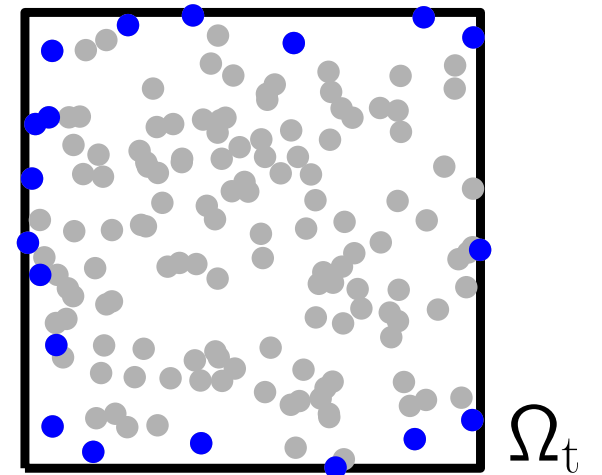
We seek to evaluate

$$\mathbf{q} \mapsto \mathbf{f} = \mathbf{A}\mathbf{q}.$$

Source locations $\{\mathbf{y}_j\}_{j=1}^n$



Target locations $\{\mathbf{x}_i\}_{i=1}^m$



Interpolative decomposition (ID): Let's do G-S on the *rows* of \mathbf{A} as well

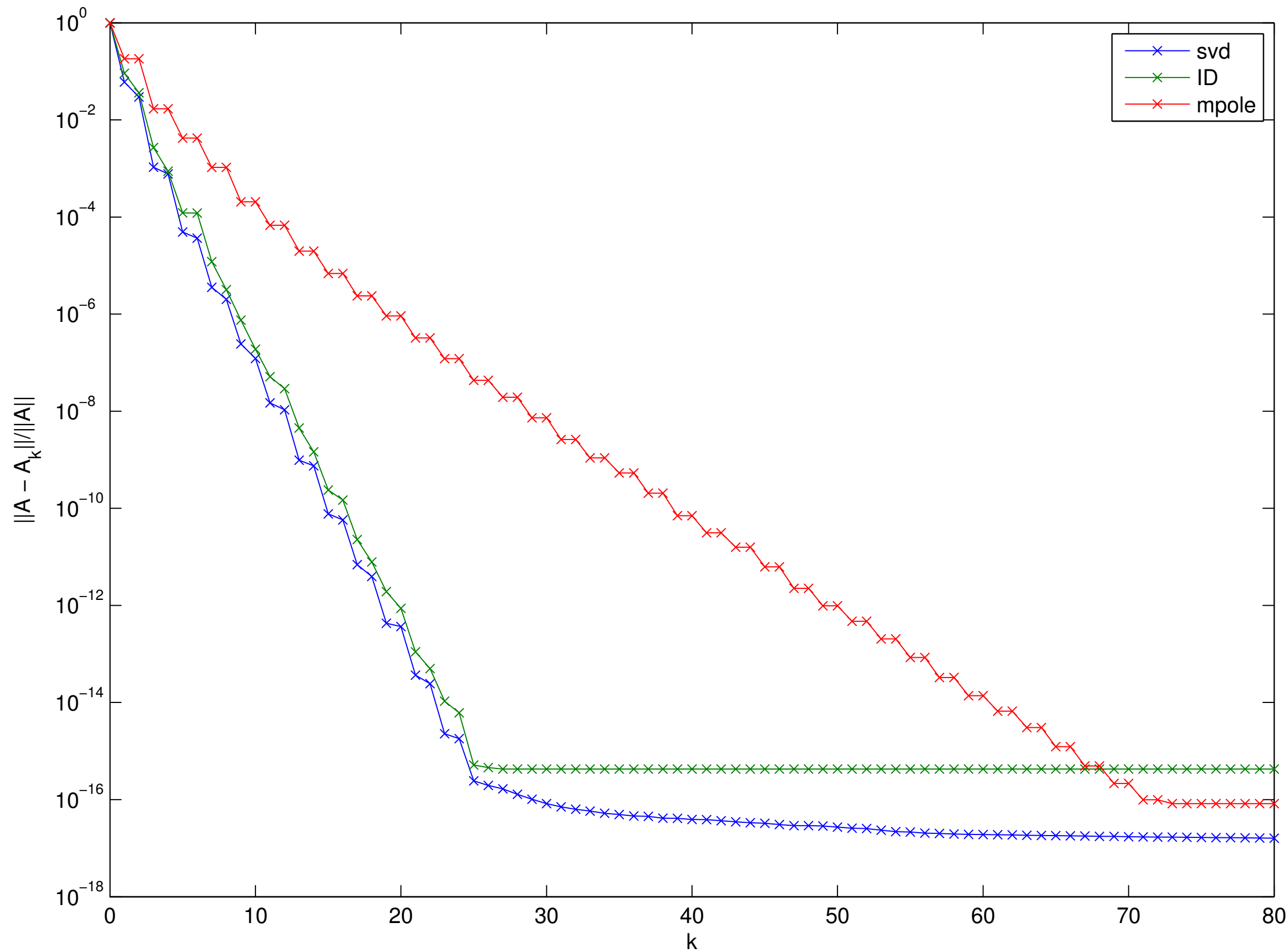
$$\begin{array}{cccc} \mathbf{A} & \approx & \mathbf{U} & \mathbf{A}^{(\text{skel})} & \mathbf{V}^* \\ m \times n & & m \times k & k \times k & k \times n \end{array}$$

where $\mathbf{A}^{(\text{skel})} = \mathbf{A}(\tilde{l}_t, \tilde{l}_s)$ is a $k \times k$ sub-matrix of \mathbf{A} .

$$\begin{array}{ccc} \mathbf{q} & \xrightarrow{\mathbf{A}} & \mathbf{f} \\ \mathbf{v}^* \downarrow & & \uparrow \mathbf{U} \\ \hat{\mathbf{q}} & \xrightarrow{\mathbf{A}^{(\text{skel})}} & \hat{\mathbf{f}} \end{array}$$

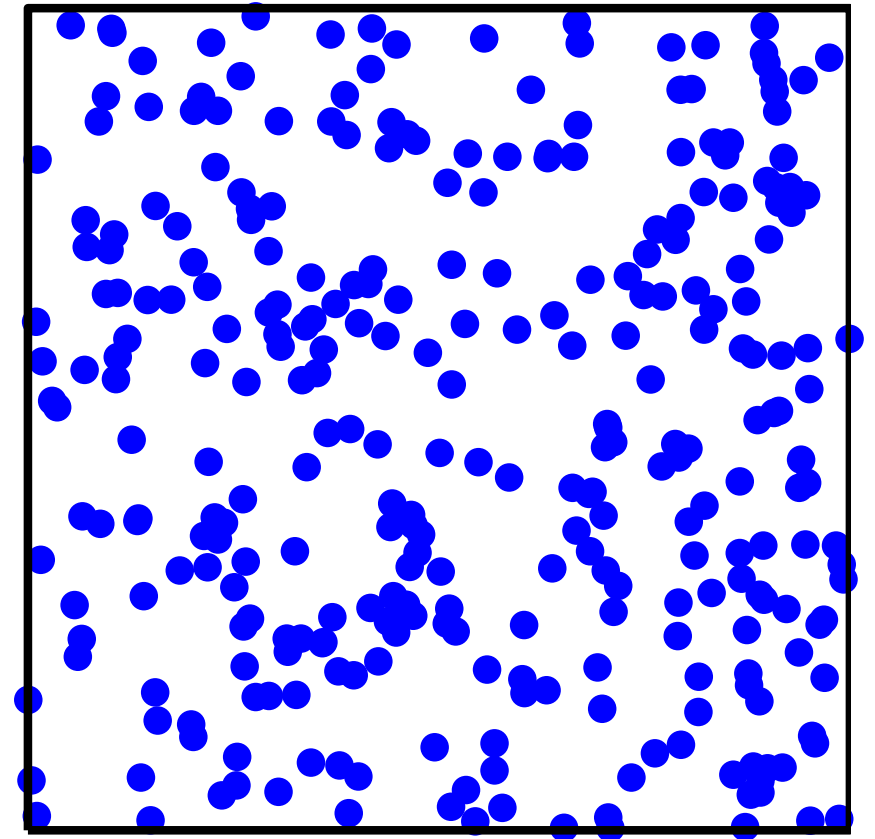
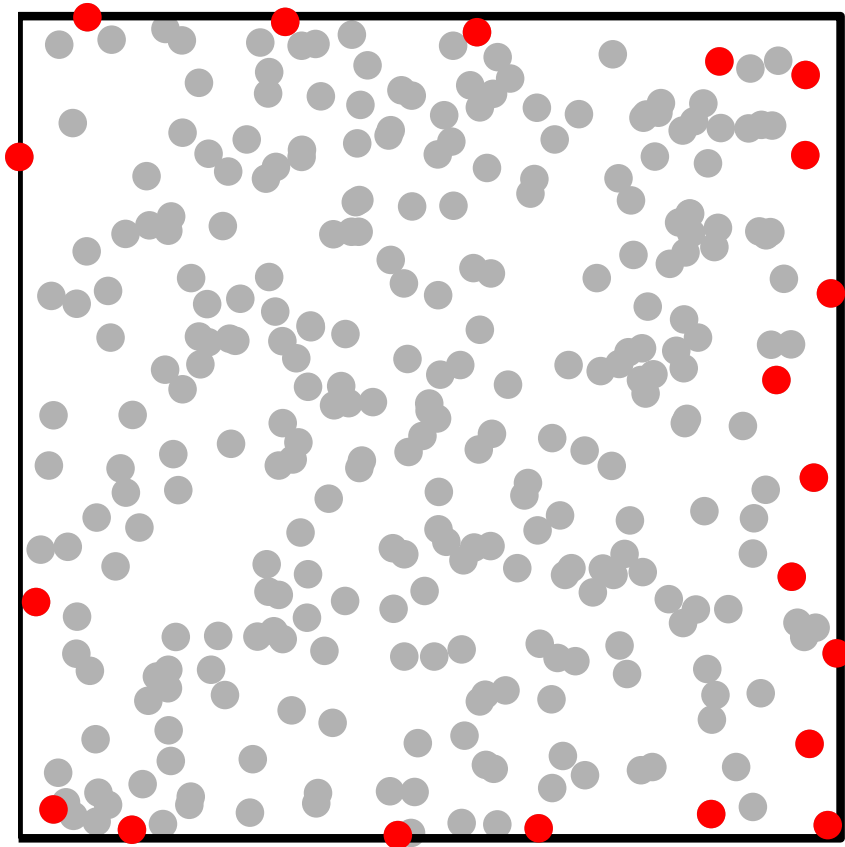
Approximation errors as a function of the rank k .

Interaction potential is Laplace, $\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|$.



The 20 skeleton points required for (relative) accuracy $\varepsilon = 10^{-12}$.

Interaction potential is Laplace, $\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|$.

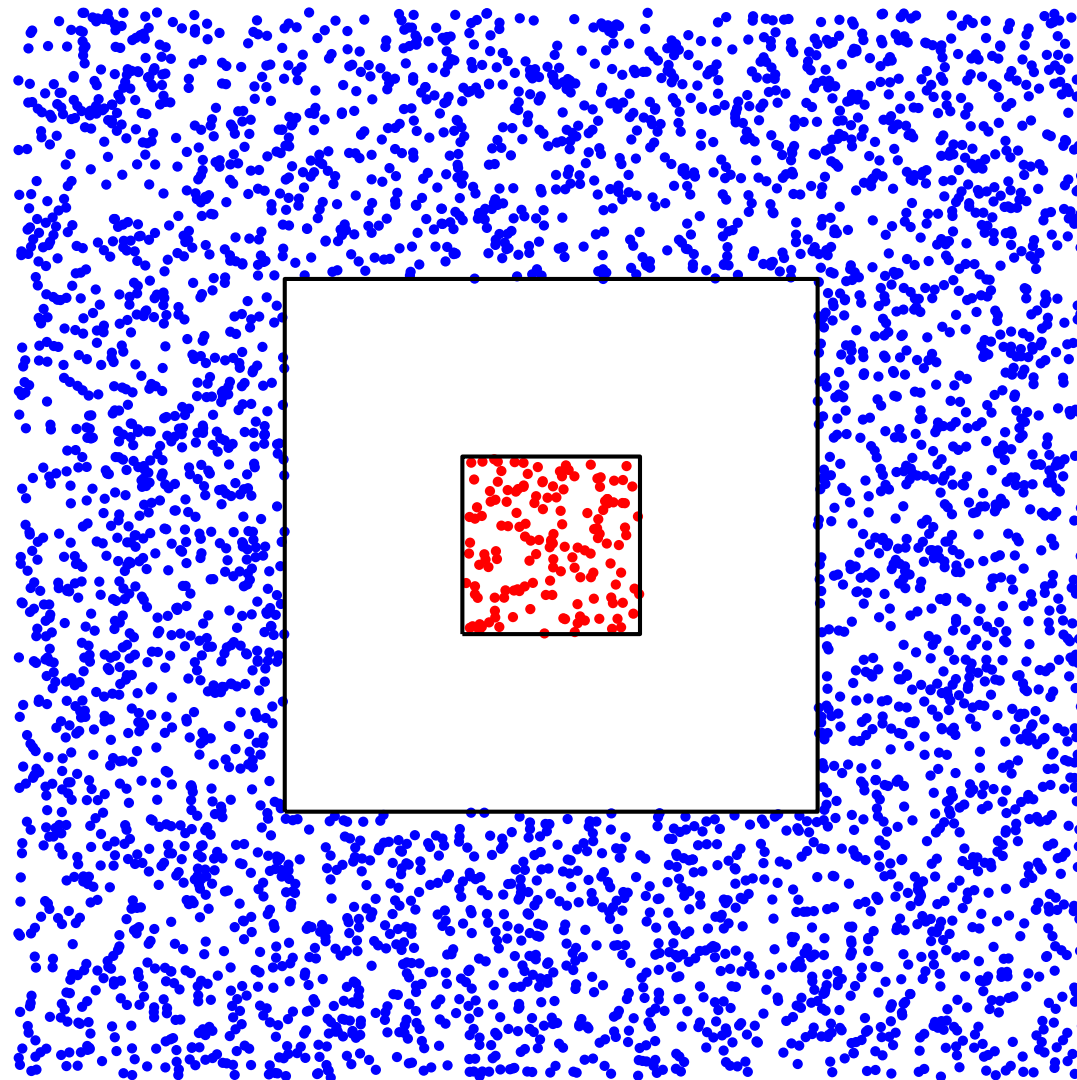


Conclusions from experiments:

- The SVD and ID are comparable in effectiveness.
(In our case! When the singular values decay slowly, this is not true.)
- The multipole expansion requires more terms.

But, the comparison is not quite fair — the multipole expansion is valid for *any* source point that is well-separated.

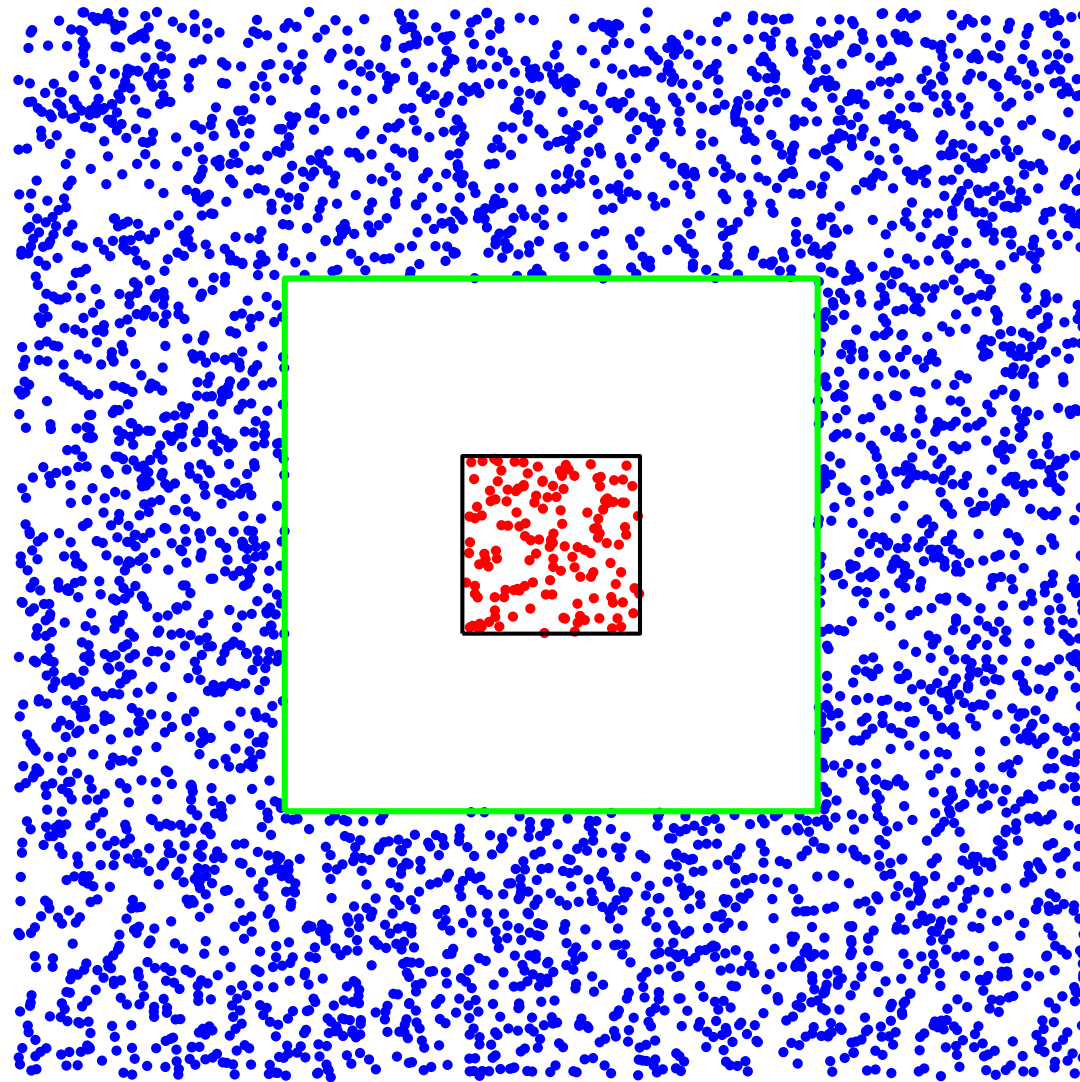
Question: Can we find skeleton points that “work” for any well-separated target point?



First observe that we do not need to consider “every” potential target point.

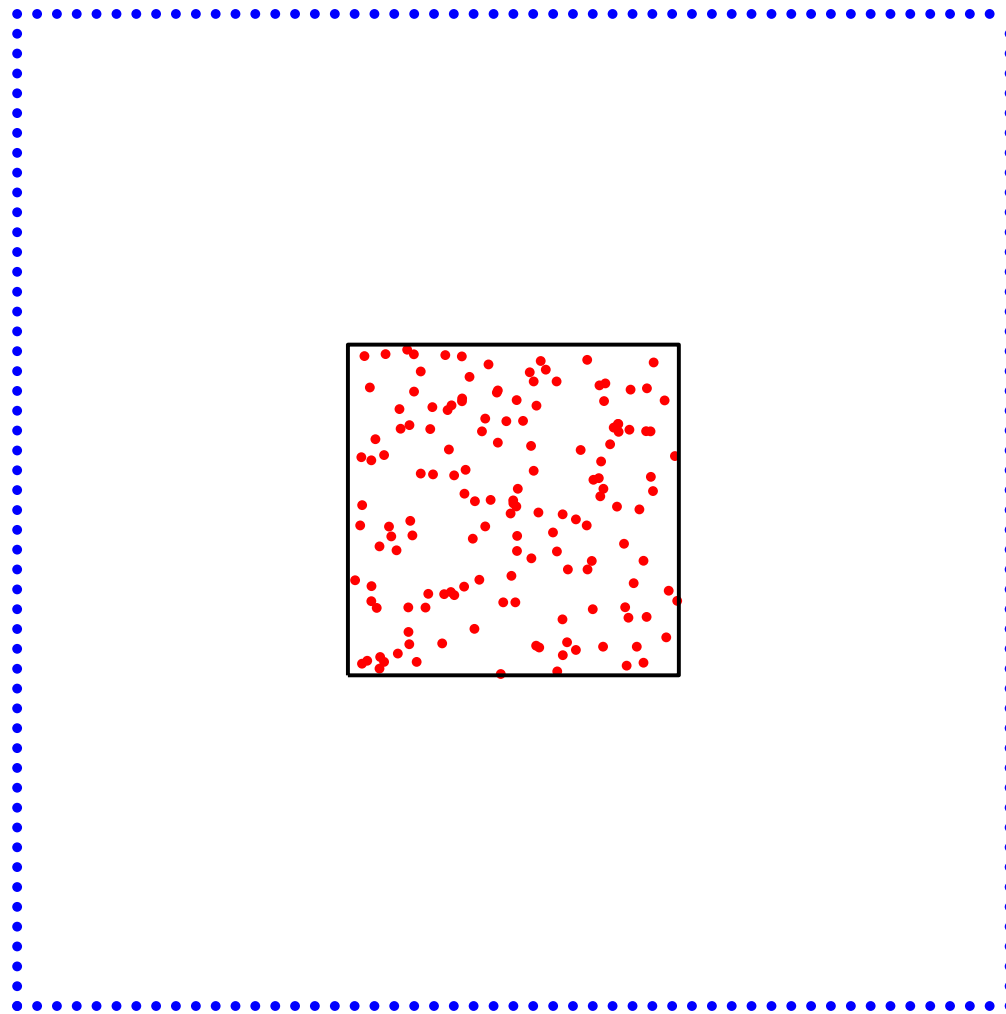
Let u denote the potential caused by the source points: $u(\mathbf{x}) = \sum_{j=1}^n q_j \log |\mathbf{x} - \mathbf{y}_j|$.

Now suppose that we can accurately reconstruct u on the green square shown:



Observe that u is harmonic (i.e. $-\Delta u = 0$) outside the green square.

Since the Laplace problem has a unique solution, we know that if we correctly reproduce u on the green square, then it is correctly reproduced *everywhere* outside the square.

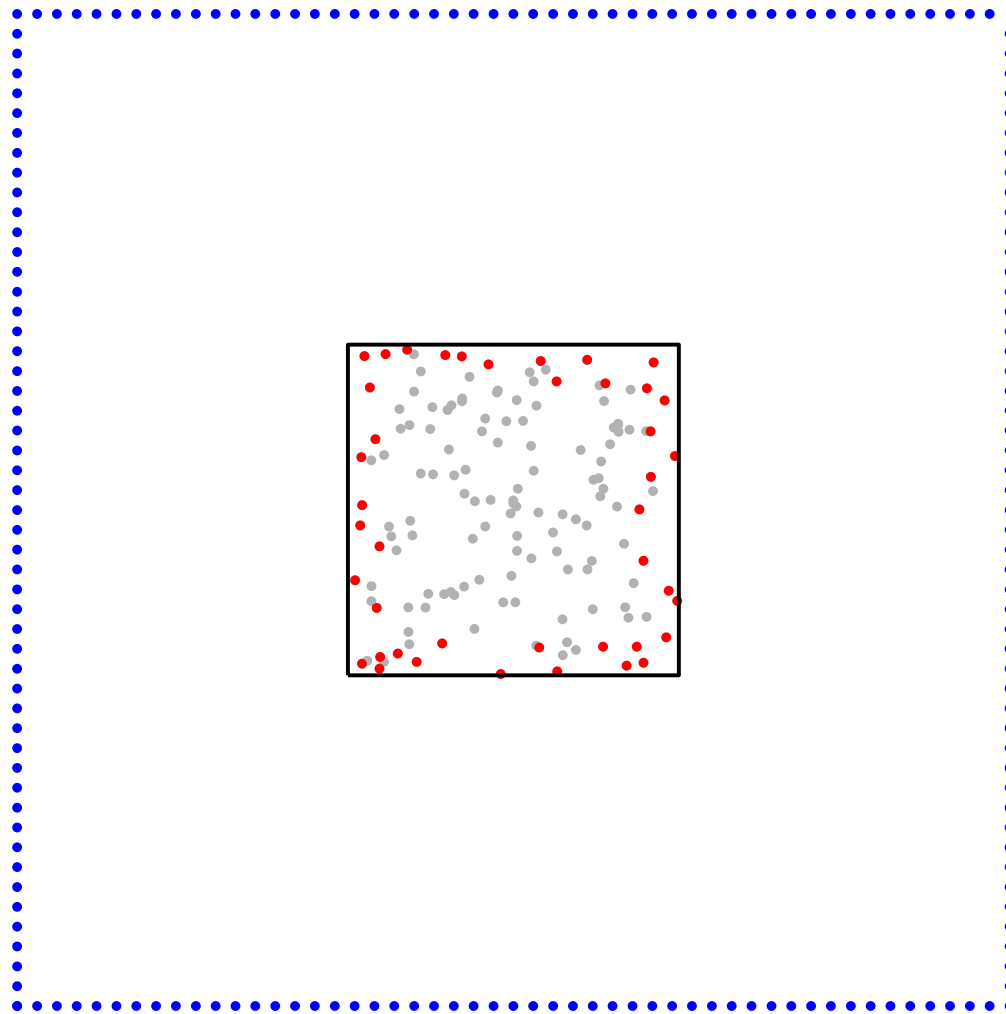


Let $\{\mathbf{y}_j\}_{j=1}^n$ be sources in the small red box.

Let $\{\mathbf{x}_i\}_{i=1}^m$ be targets on the large blue box.

Let \mathbf{A} be the matrix with elements $\mathbf{A}(i, j) = \log |\mathbf{x}_i - \mathbf{y}_j|$.

Perform Gram-Schmidt on the columns of \mathbf{A} ,



Let $\{\mathbf{y}_j\}_{j=1}^n$ be sources in the small red box.

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Perform Gram-Schmidt on the columns of \mathbf{A} ,

$$\mathbf{A} \approx \mathbf{A}^{(\text{skel})} \mathbf{V}^*$$

$$m \times n \quad m \times k \quad k \times n$$

We *know* that (to within precision ε), this skeleton is valid at any well-separated point.

For $\varepsilon = 10^{-12}$, we now have $k = 45$. It as $k = 20$ for the two-box geometry.

One concern remains: So far, we've looked at a given distribution of source locations. The skeleton points chosen are not "universal".

To address this issue, we will henceforth investigate the *continuum operator* A :

$$f(\mathbf{x}) = [Aq](\mathbf{x}) = \int_{\Omega_s} \log |\mathbf{x} - \mathbf{y}| q(\mathbf{y}) d\mathbf{y}, \quad \mathbf{x} \in \Omega_t$$

which maps a source distribution q in a source domain Ω_s to a potential f in a target domain Ω_t .

Let $\{\mathbf{x}_i, v_i\}_{i=1}^m$ be a quadrature for the target domain, and let $\{\mathbf{y}_j, w_j\}_{j=1}^n$ be a quadrature for the source domain.

Let the vector \mathbf{f} have entries $\mathbf{f}(i) = \sqrt{v_i} f(\mathbf{x}_i)$ so that $\|f\|_{L^2(\Omega_t)} \approx \|\mathbf{f}\|_{\ell^2}$.

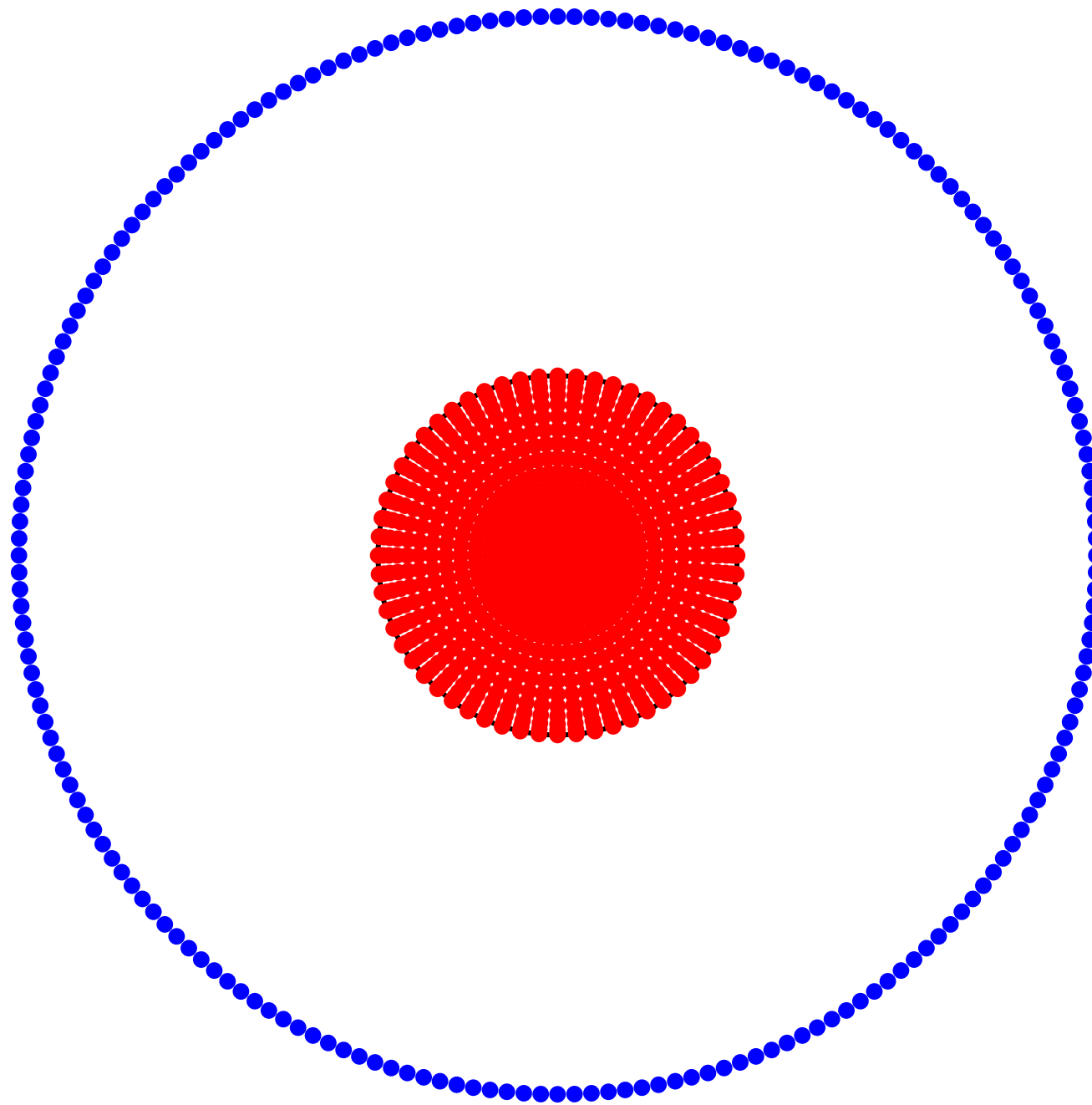
Let the vector \mathbf{q} have entries $\mathbf{q}(j) = \sqrt{w_j} q(\mathbf{y}_j)$ so that $\|q\|_{L^2(\Omega_s)} \approx \|\mathbf{q}\|_{\ell^2}$.

Finally, let \mathbf{A} be the $m \times n$ matrix with entries $\mathbf{A}(i, j) = \sqrt{v_i} \log |\mathbf{x}_i - \mathbf{y}_j| \sqrt{w_j}$.

Then the singular values/vectors of \mathbf{A} are accurate approximations of the singular values/vectors of A .

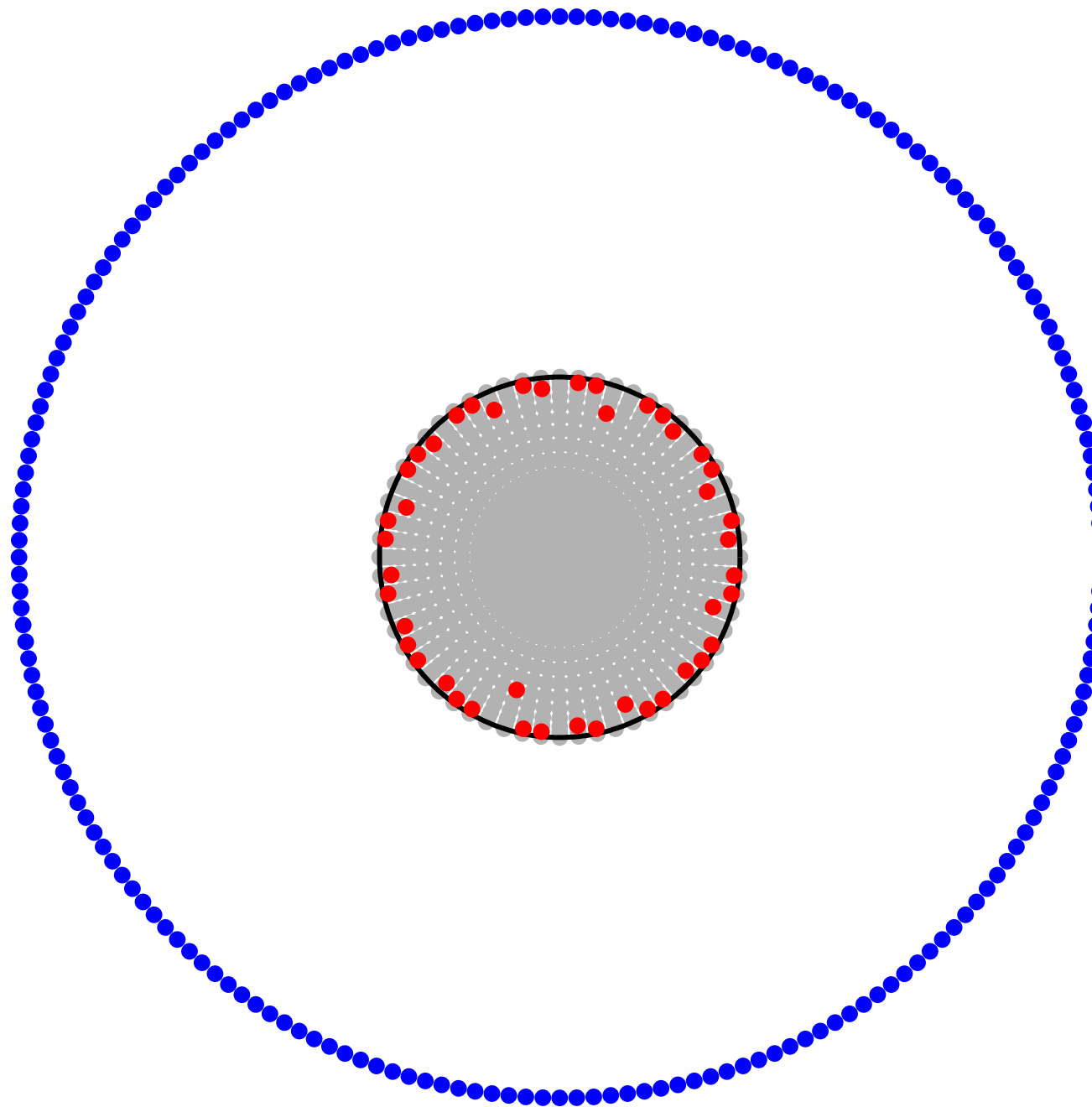
Observe that when Ω_s and Ω_t are not "too close," the kernel $\log |\mathbf{x} - \mathbf{y}|$ is smooth.

Example: Two concentric circles — ideal for multipole expansion.



Sources in a disc of radius 0.5, targets on a circle of radius 1.5.

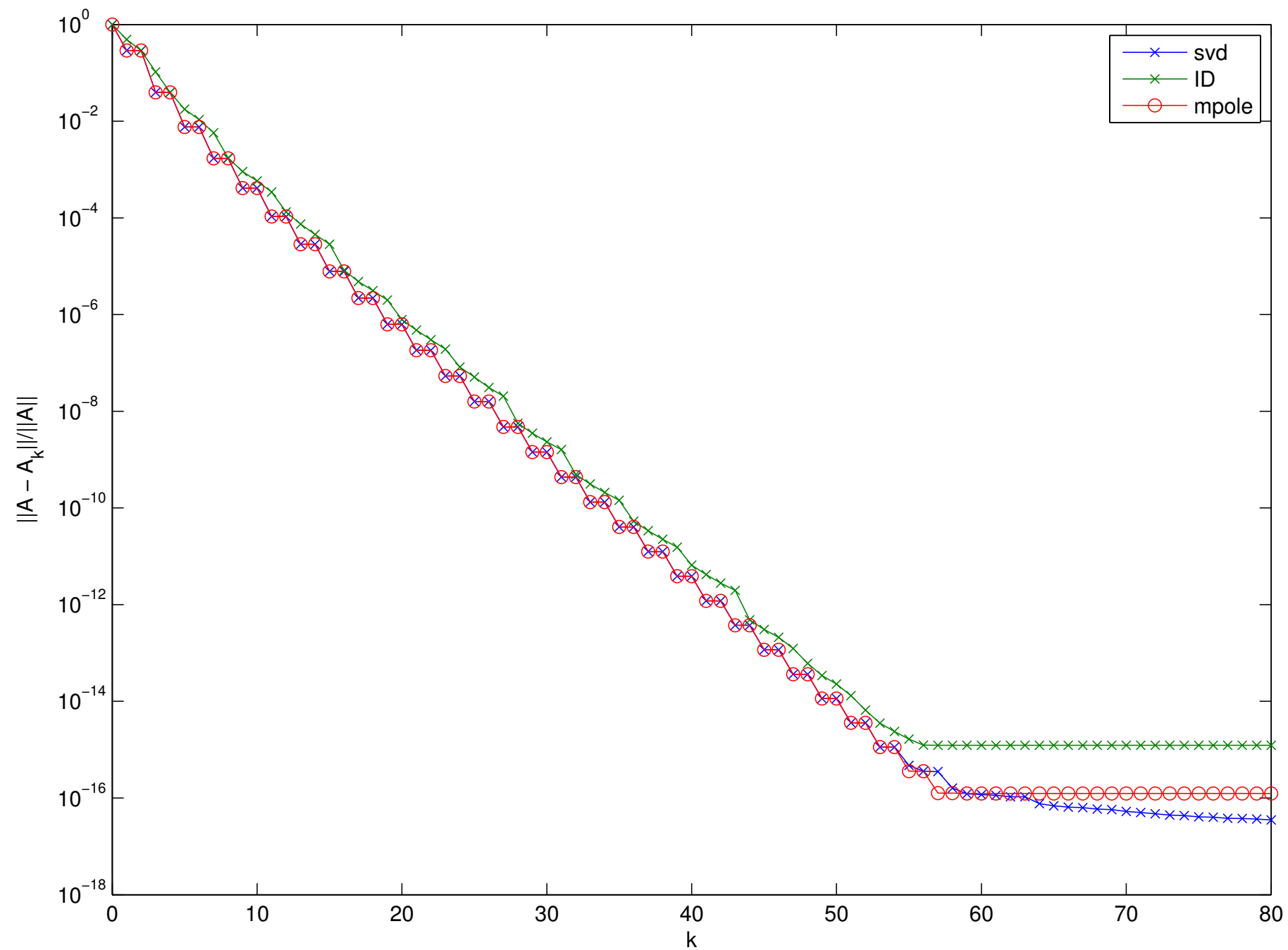
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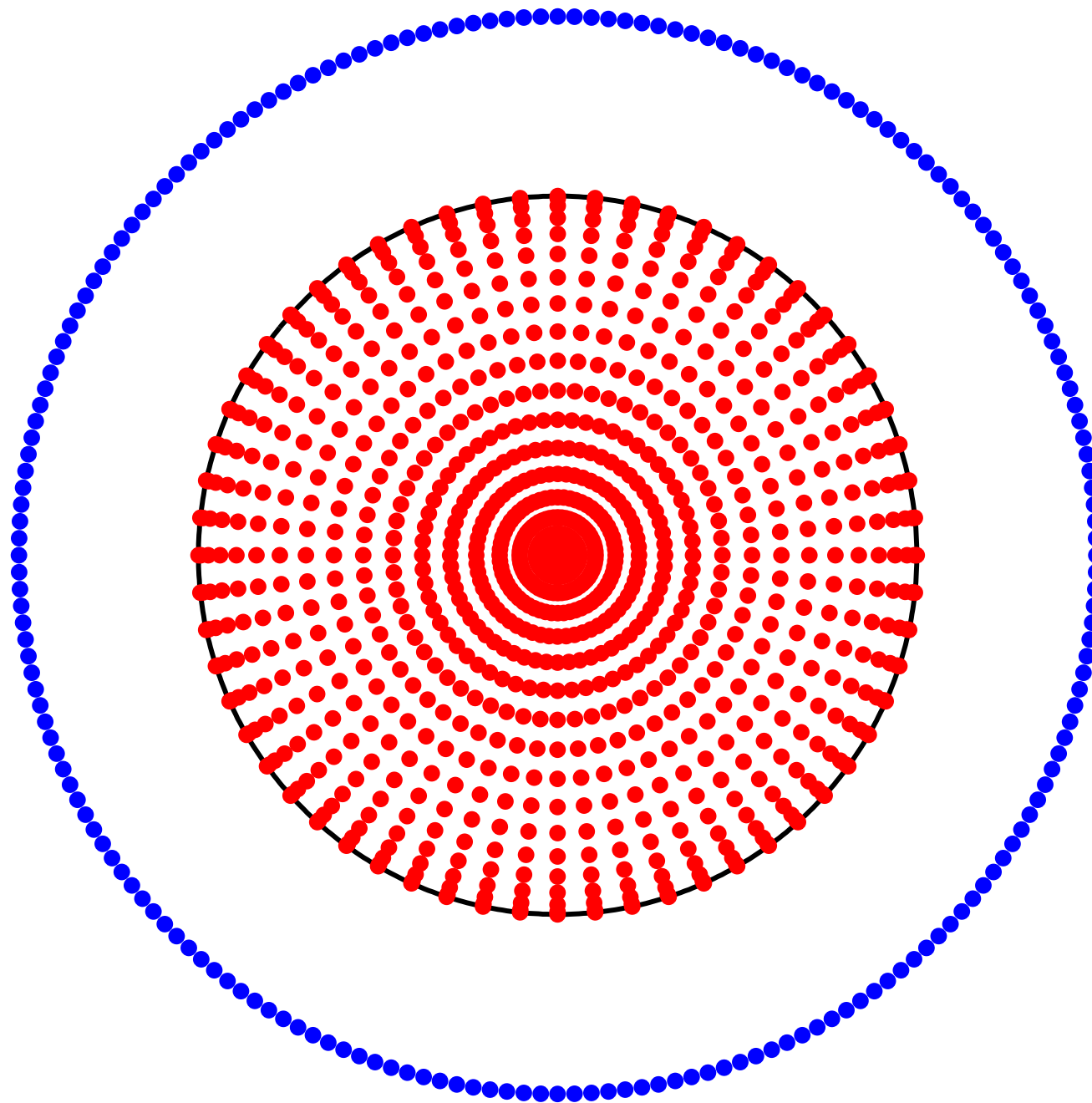
Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 44$.

Example: Two concentric circles — ideal for multipole expansion.



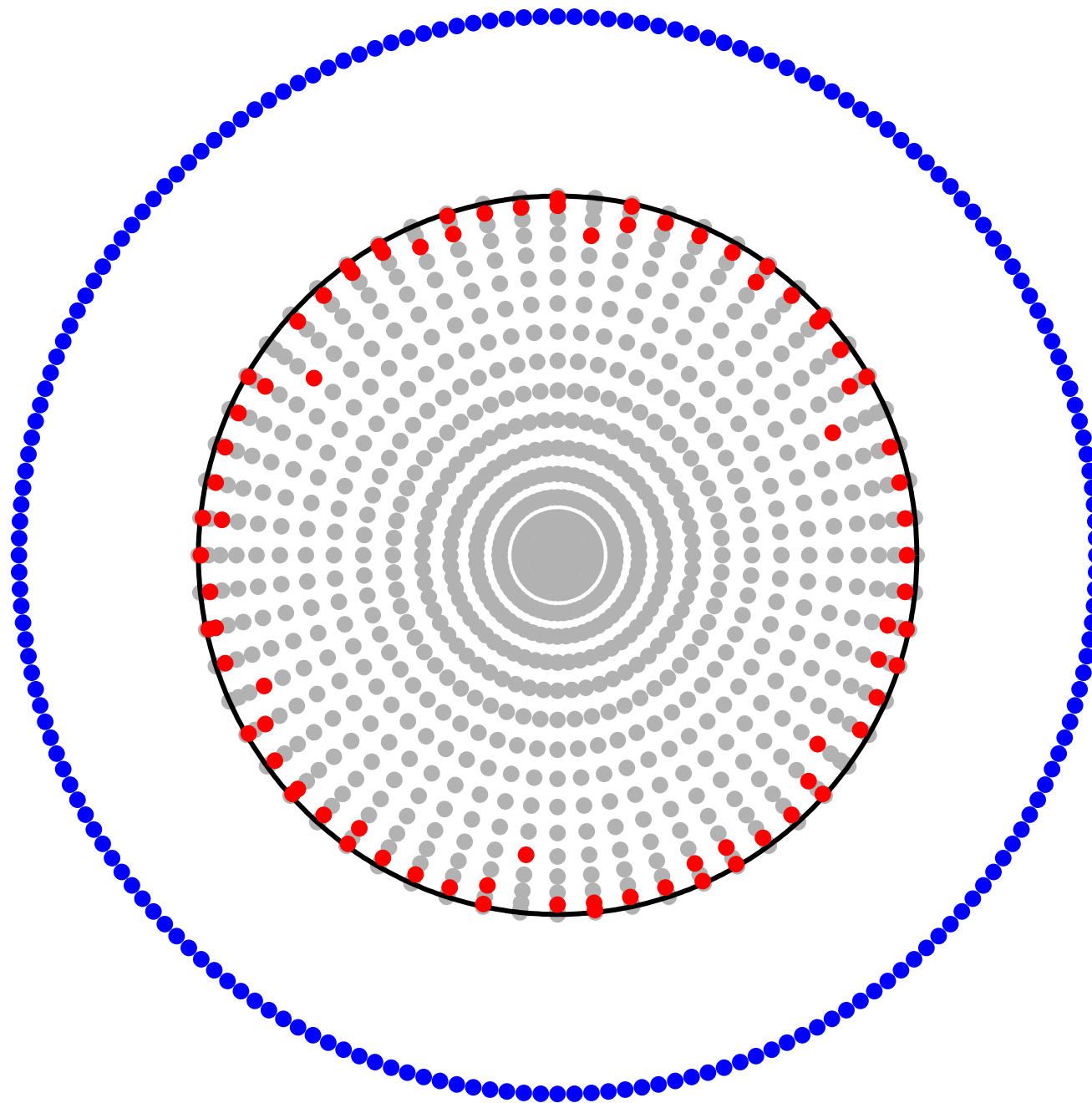
Errors. For this geometry, $E_{\text{mpole}} = E_{\text{svd}}$ exactly!

Example: Two concentric circles — now much tighter.



Sources in a disc of radius 0.5, targets on a circle of radius 0.75.

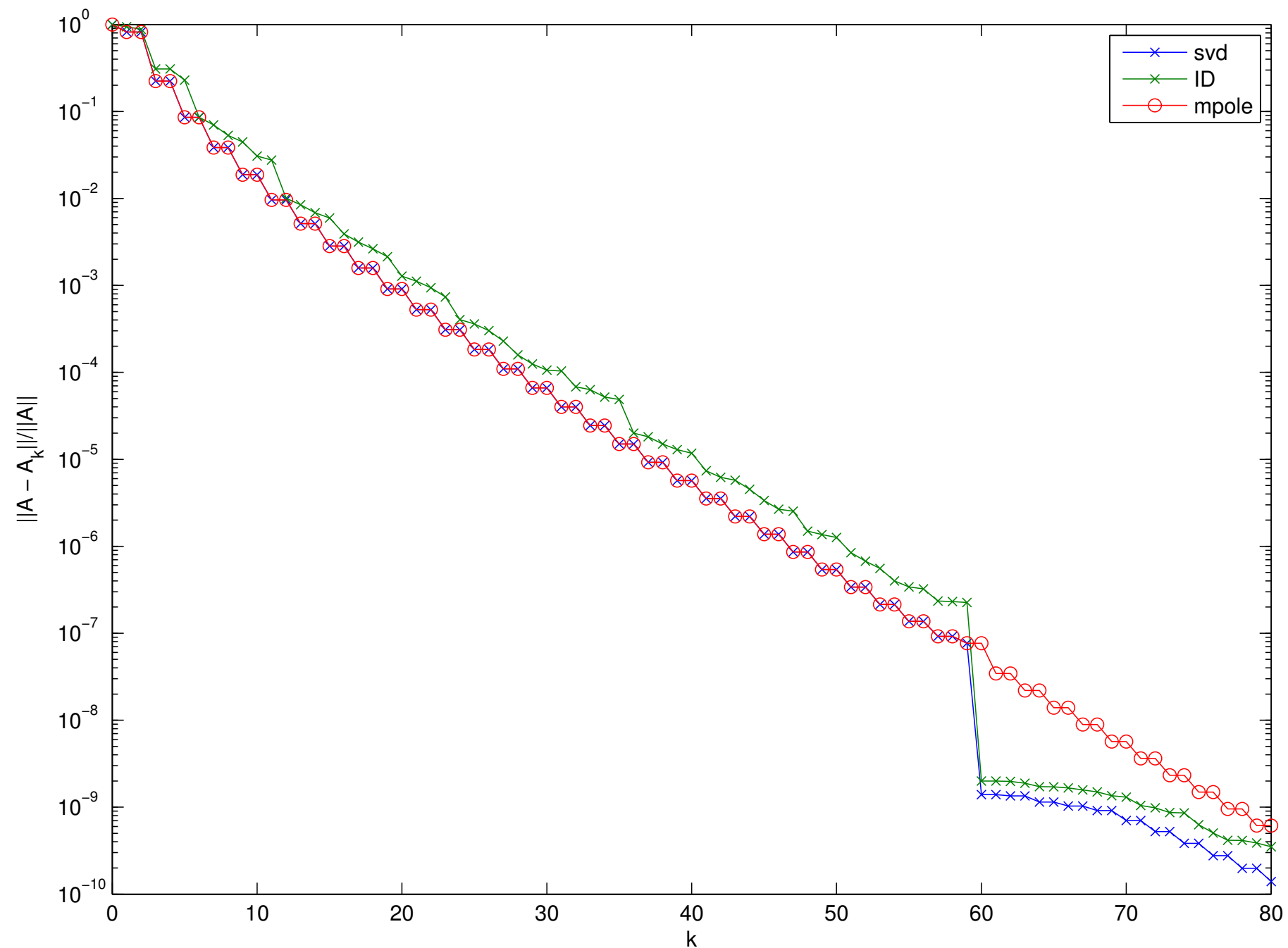
Example: Two concentric circles — now much tighter.



Sources in a disc of radius 0.5, targets on a circle of radius 1.5.

Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 81$.

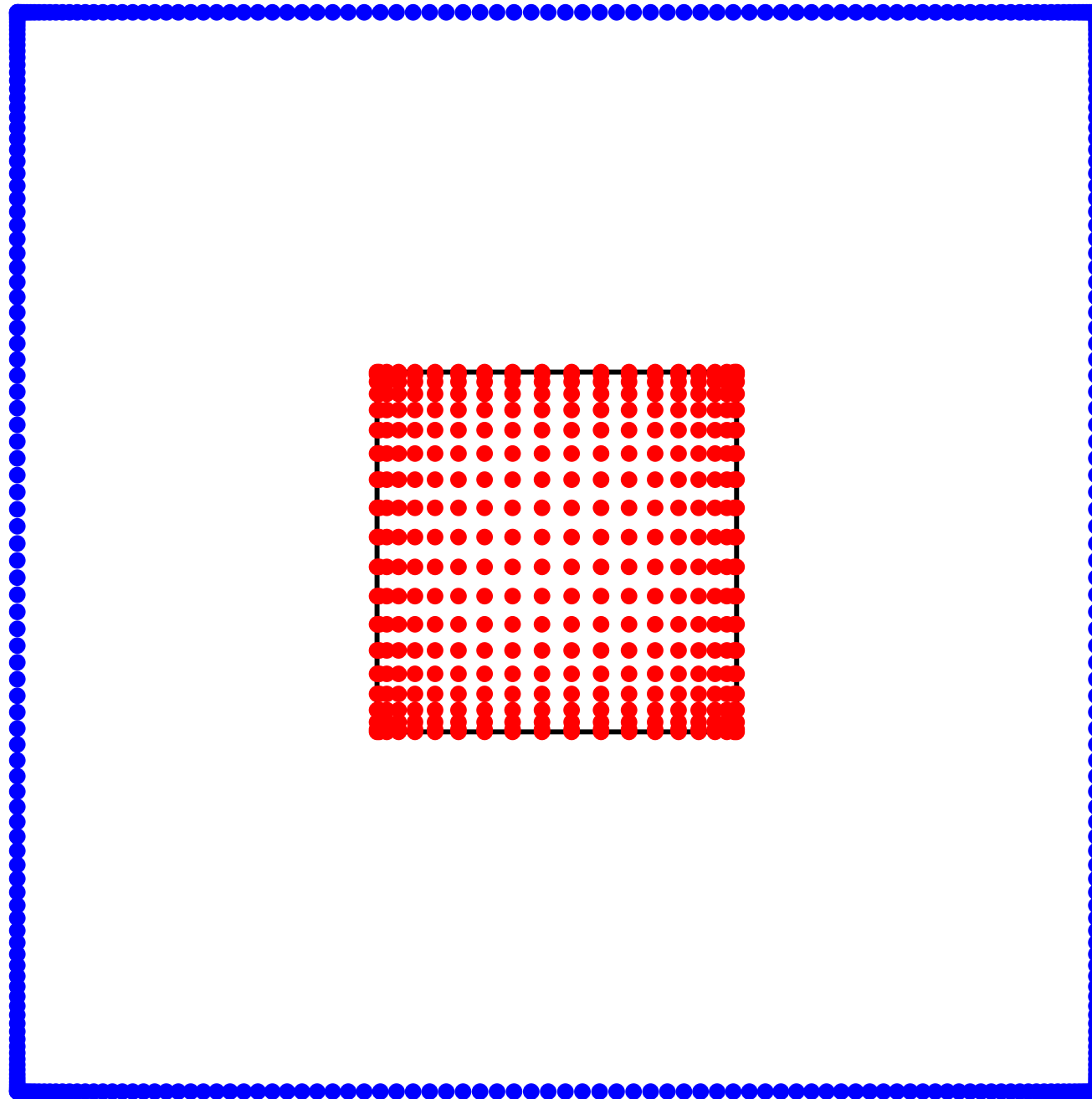
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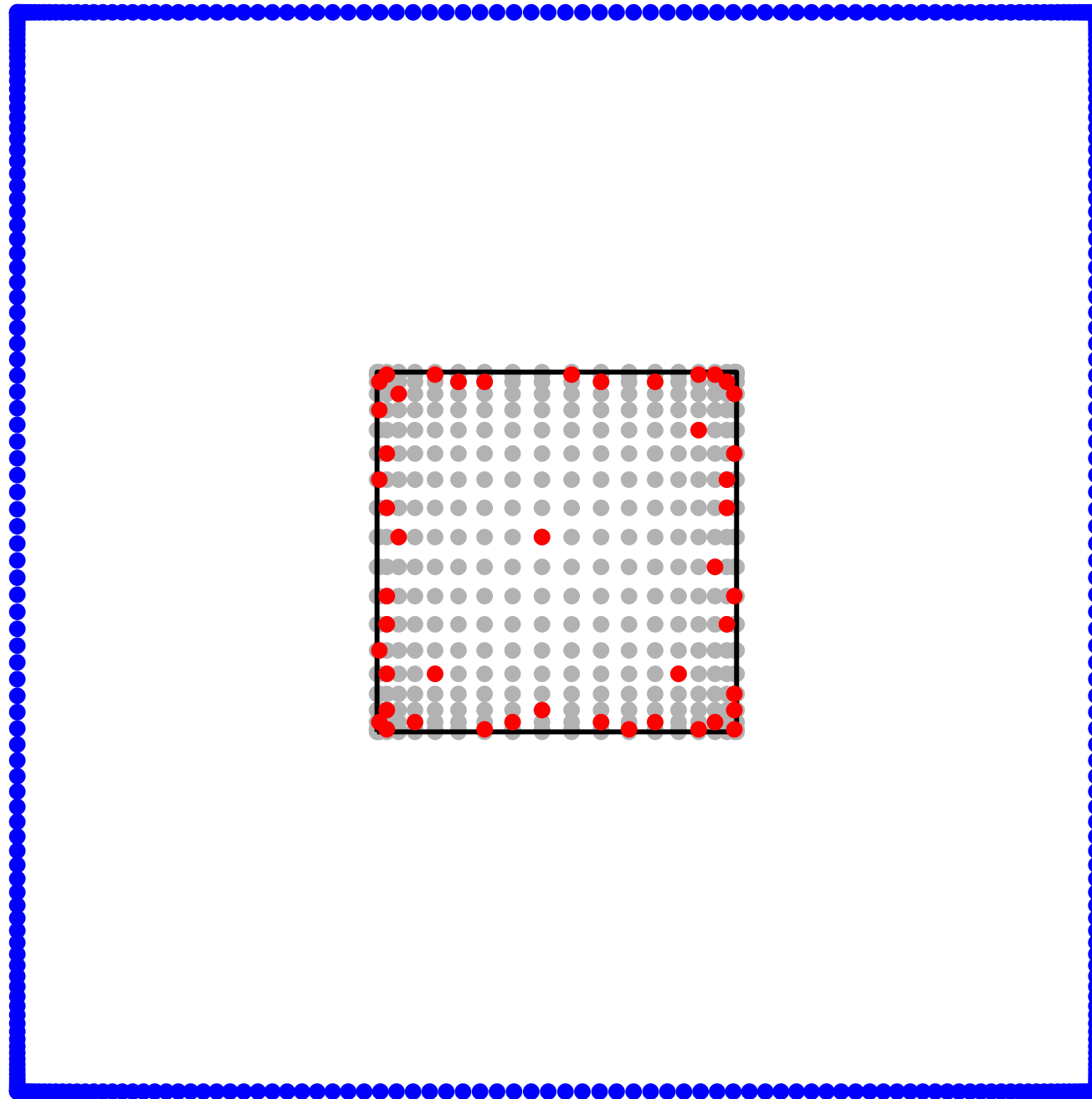
(The weirdness at the end reflects the discretization error.)

Example: Two squares — realistic FMM geometry.



Sources in a box of side length 1, targets on a box of side length 3.

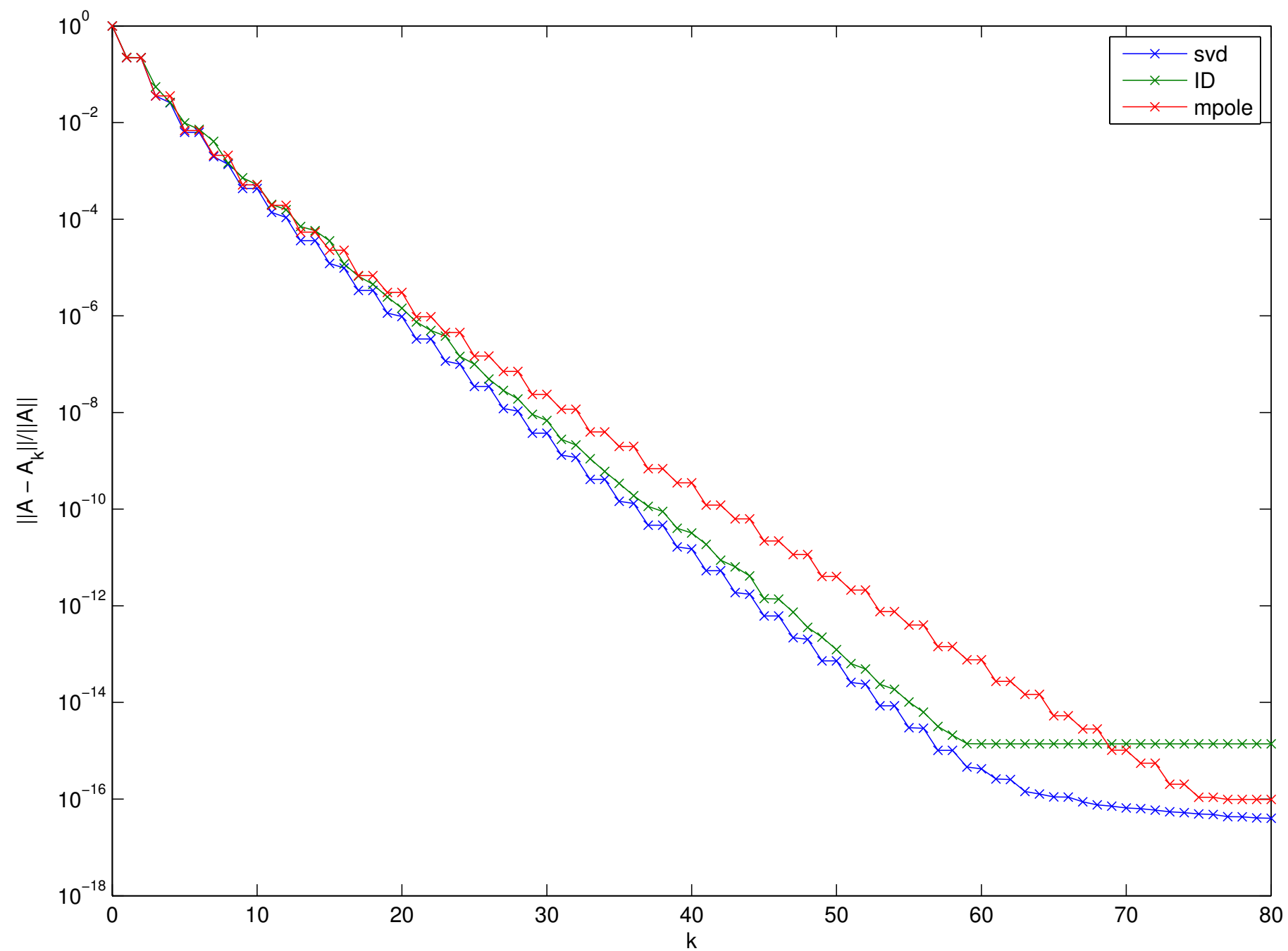
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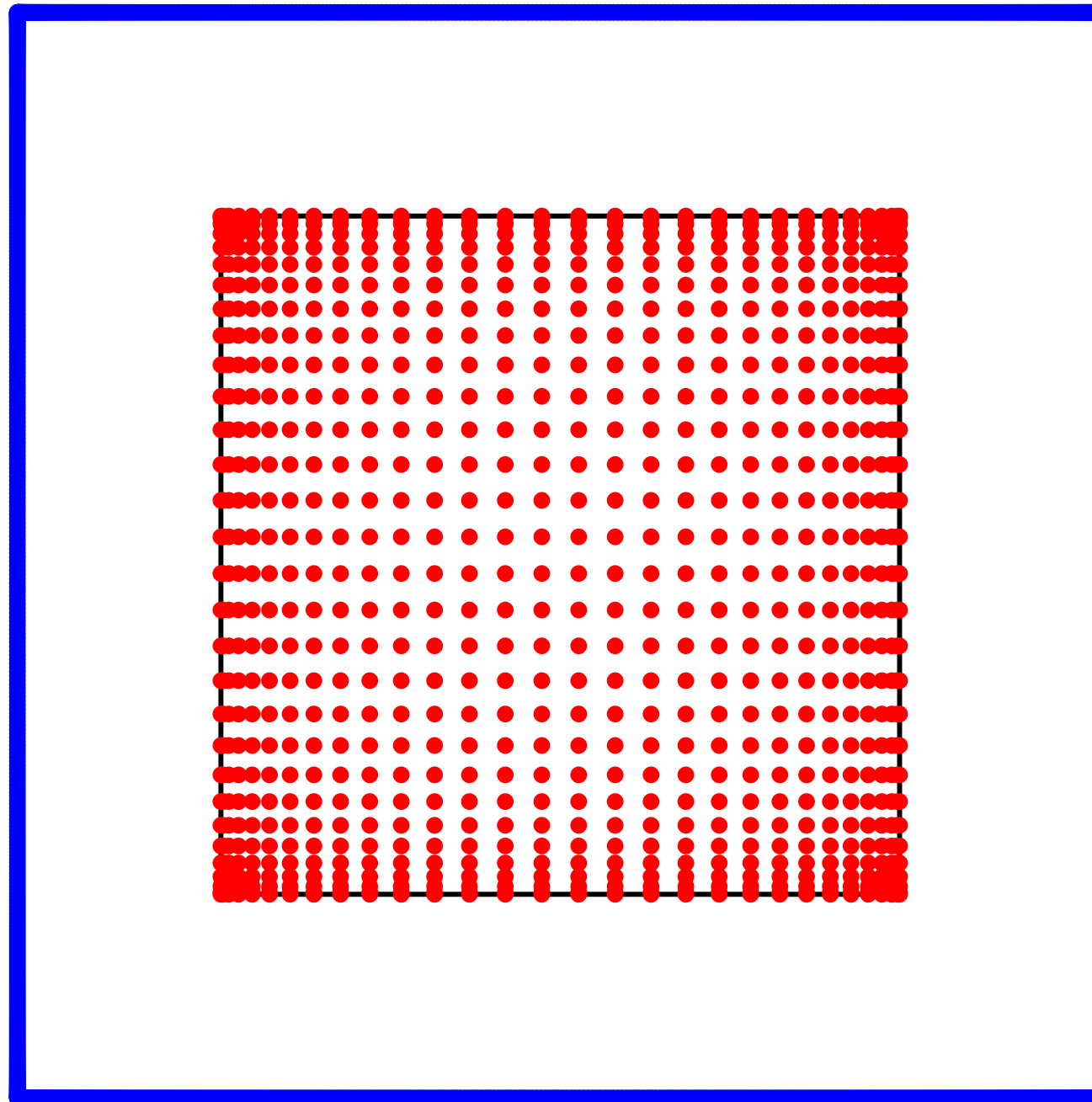
Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 47$.

Example: Two squares — realistic FMM geometry.



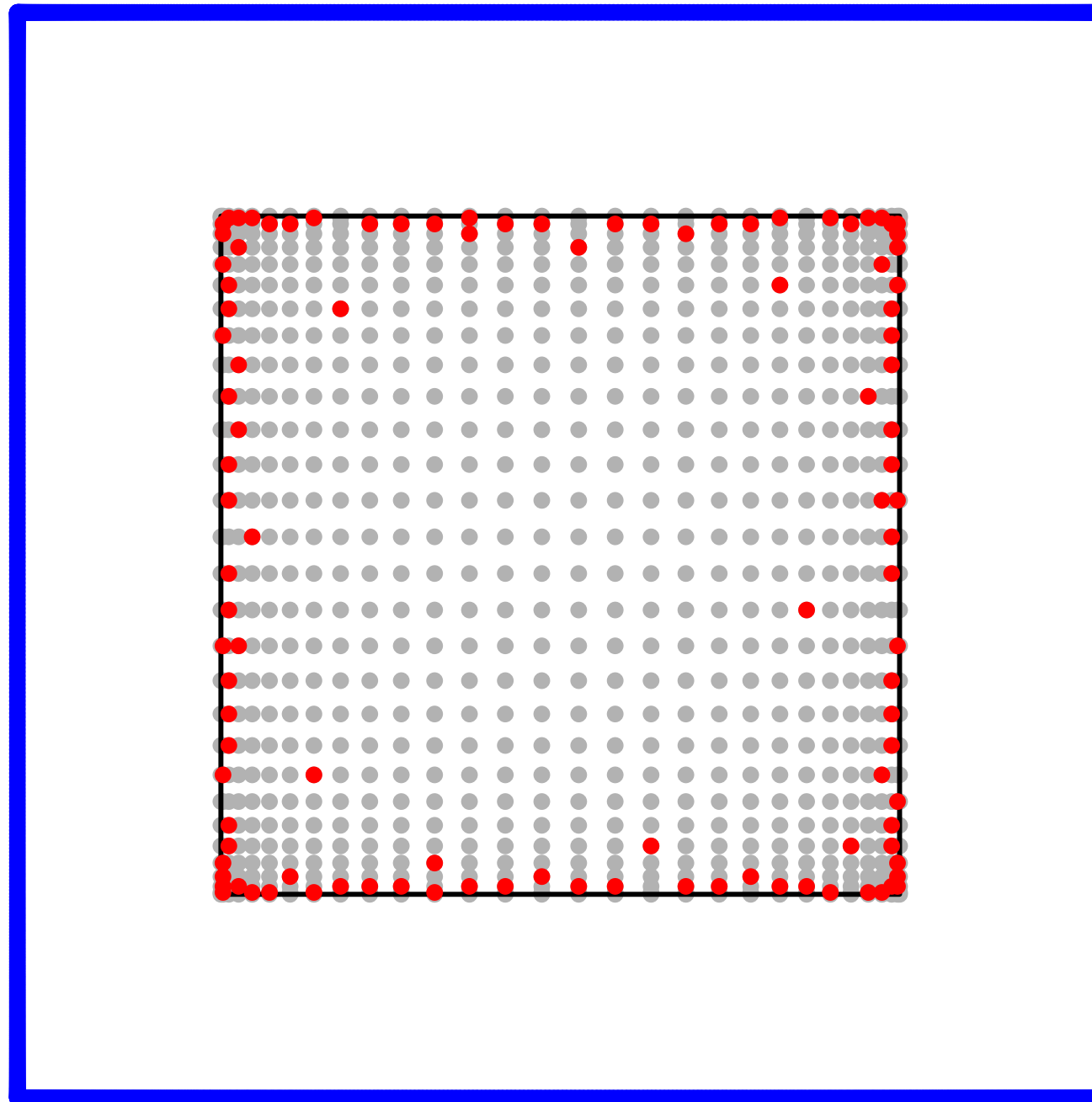
Errors.

Example: Two squares — now tighter.



Sources in a box of side length 1, targets on a box of side length 1.6.

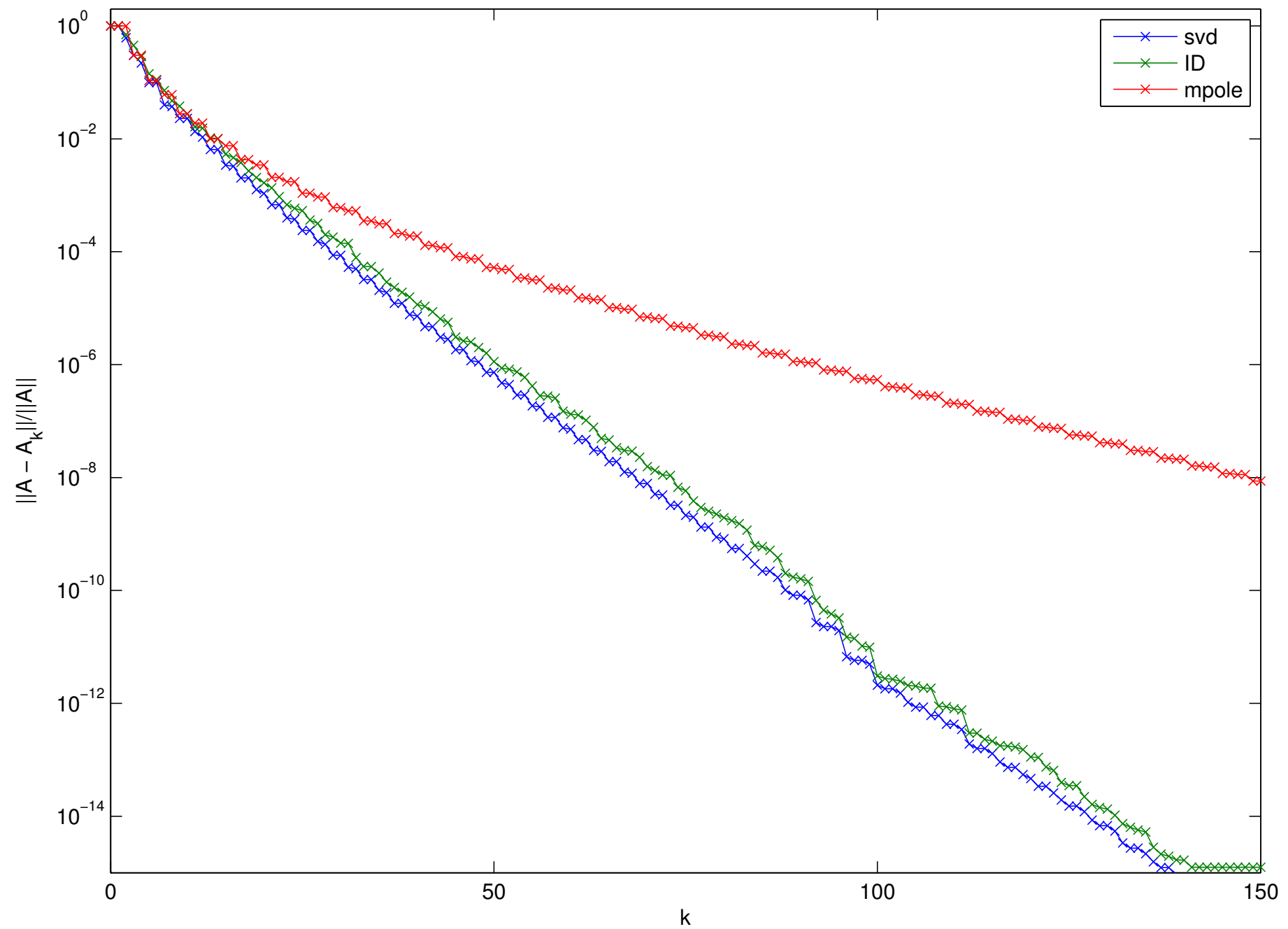
Example: Two squares — now tighter.



Sources in a box of side length 1, targets on a box of side length 1.6.

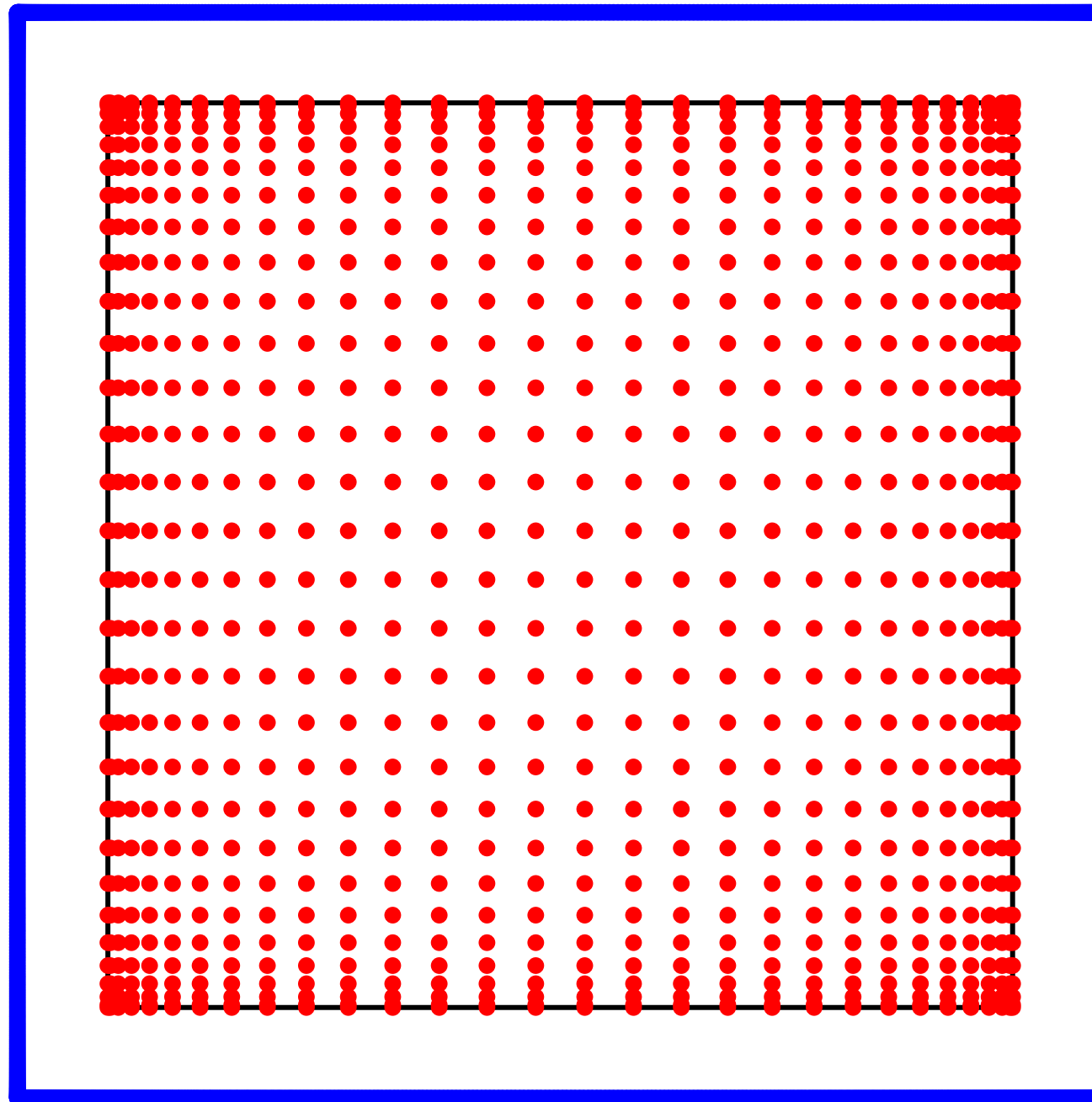
Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 108$.

Example: Two squares — now tighter.



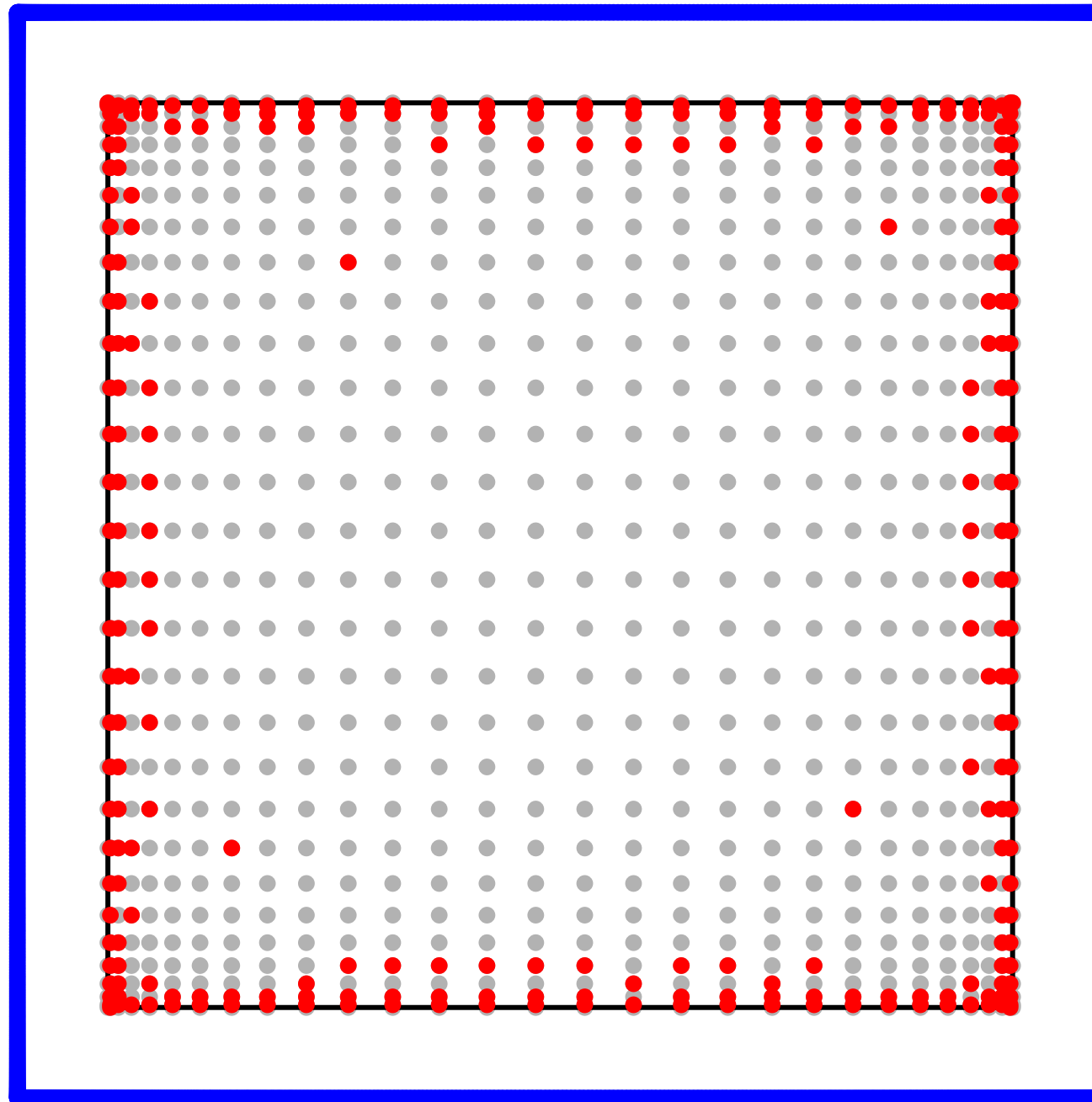
Sources in a box of side length 1, targets on a box of side length 1.6.

Example: Two squares — now even tighter.



Sources in a box of side length 1, targets on a box of side length 1.2.

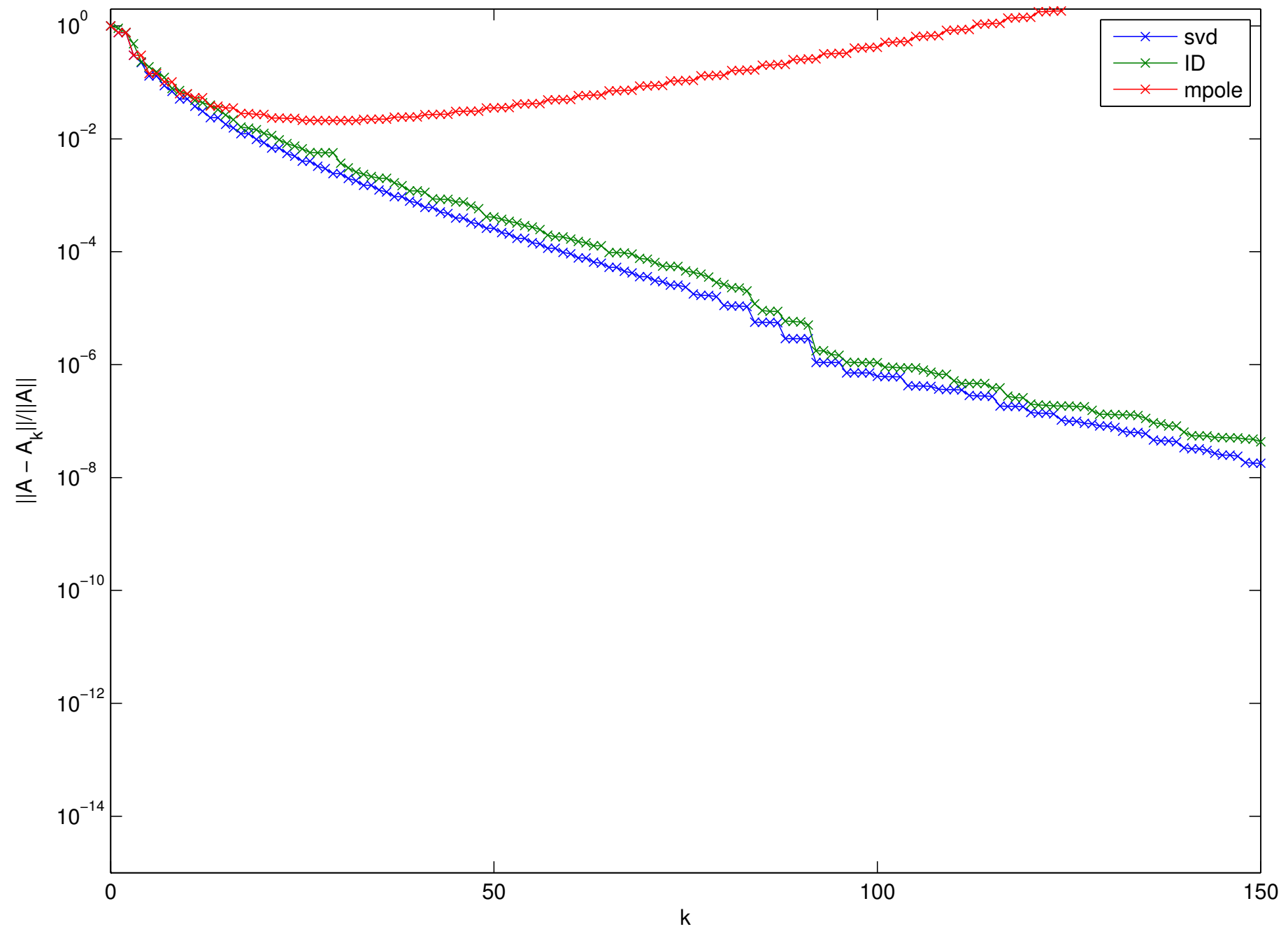
Example: Two squares — now even tighter.



Sources in a box of side length 1, targets on a box of side length 1.2.

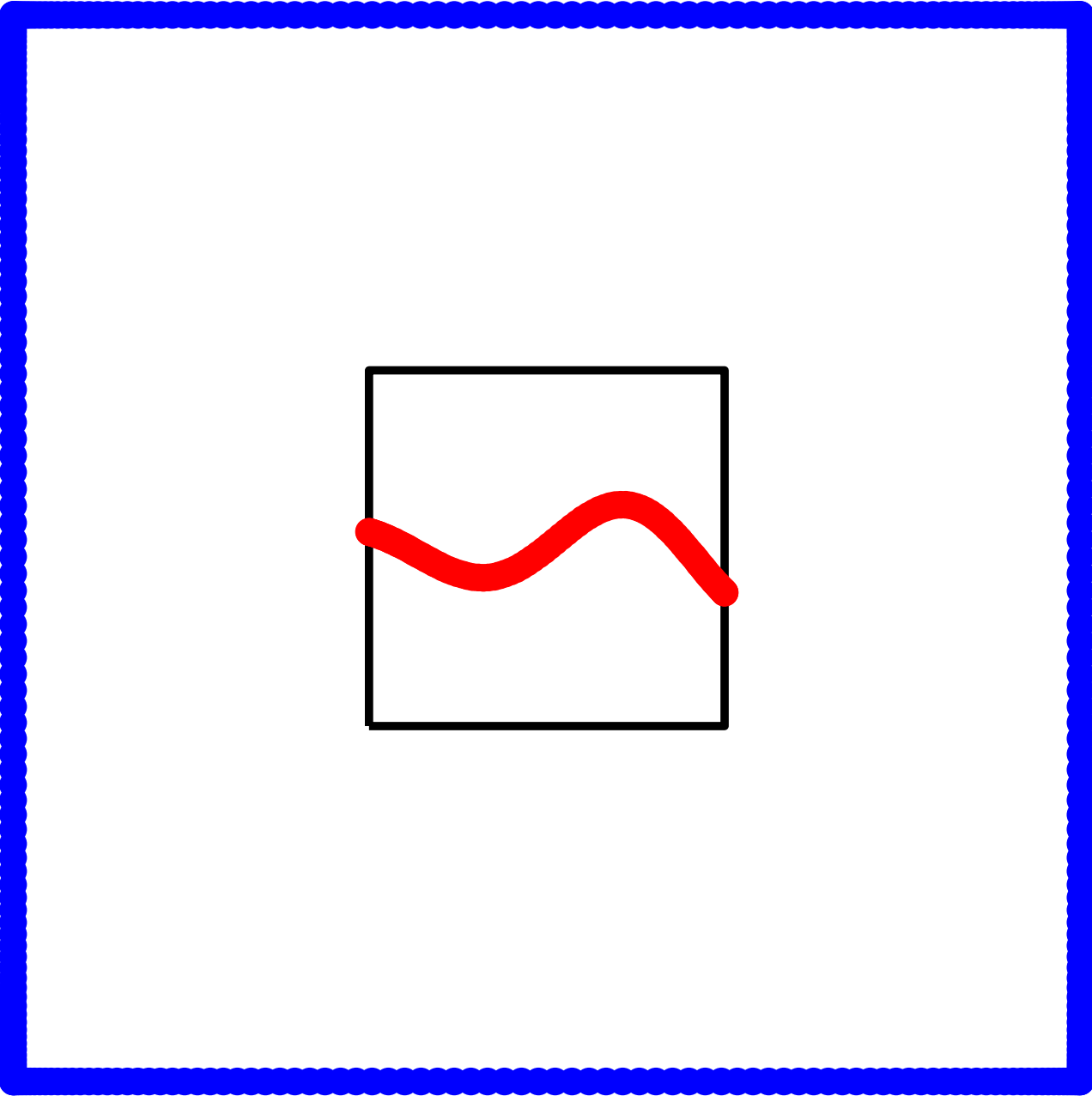
Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 260$.

Example: Two squares — now even tighter.

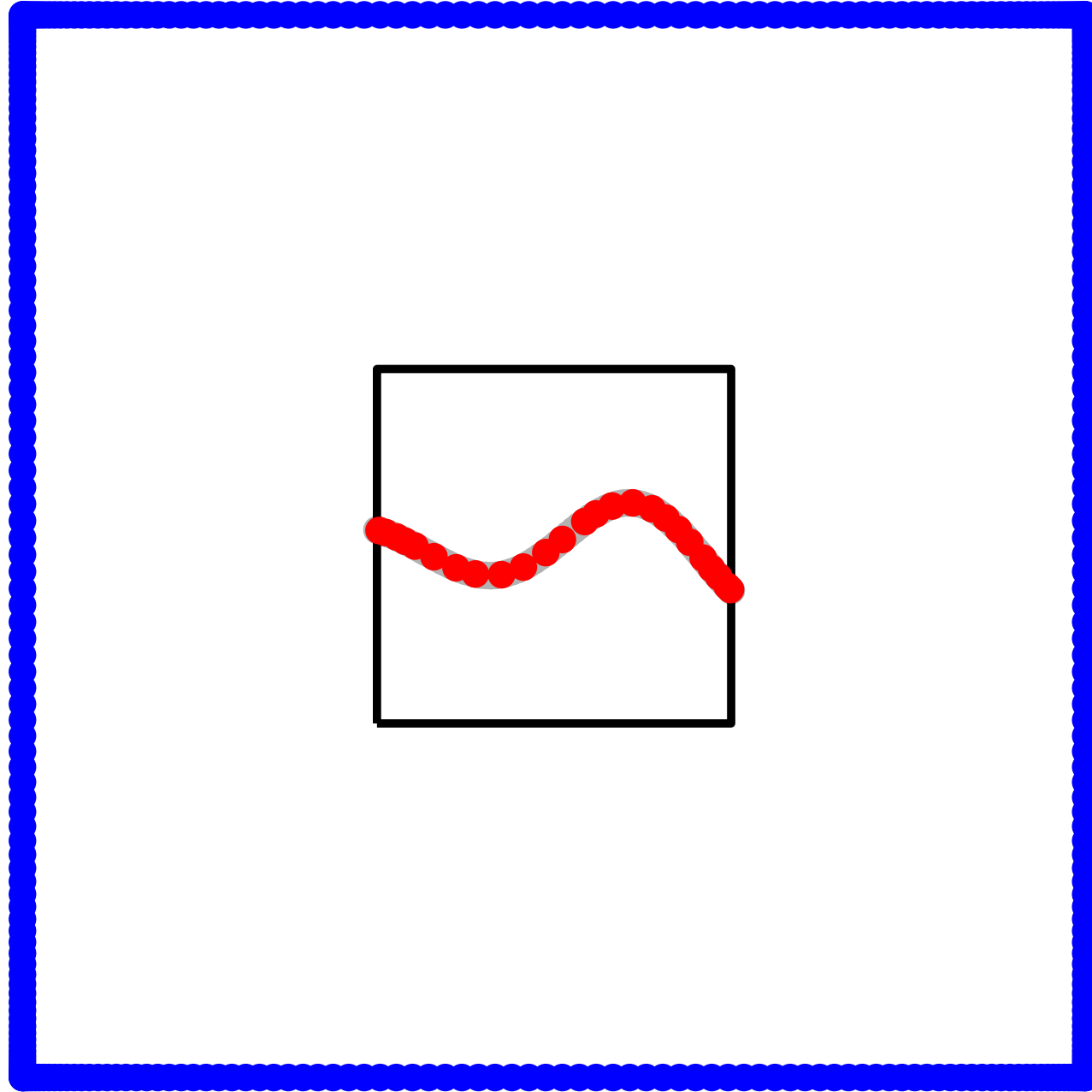


Sources in a box of side length 1, targets on a box of side length 1.2.

Example: A piece of a contour.

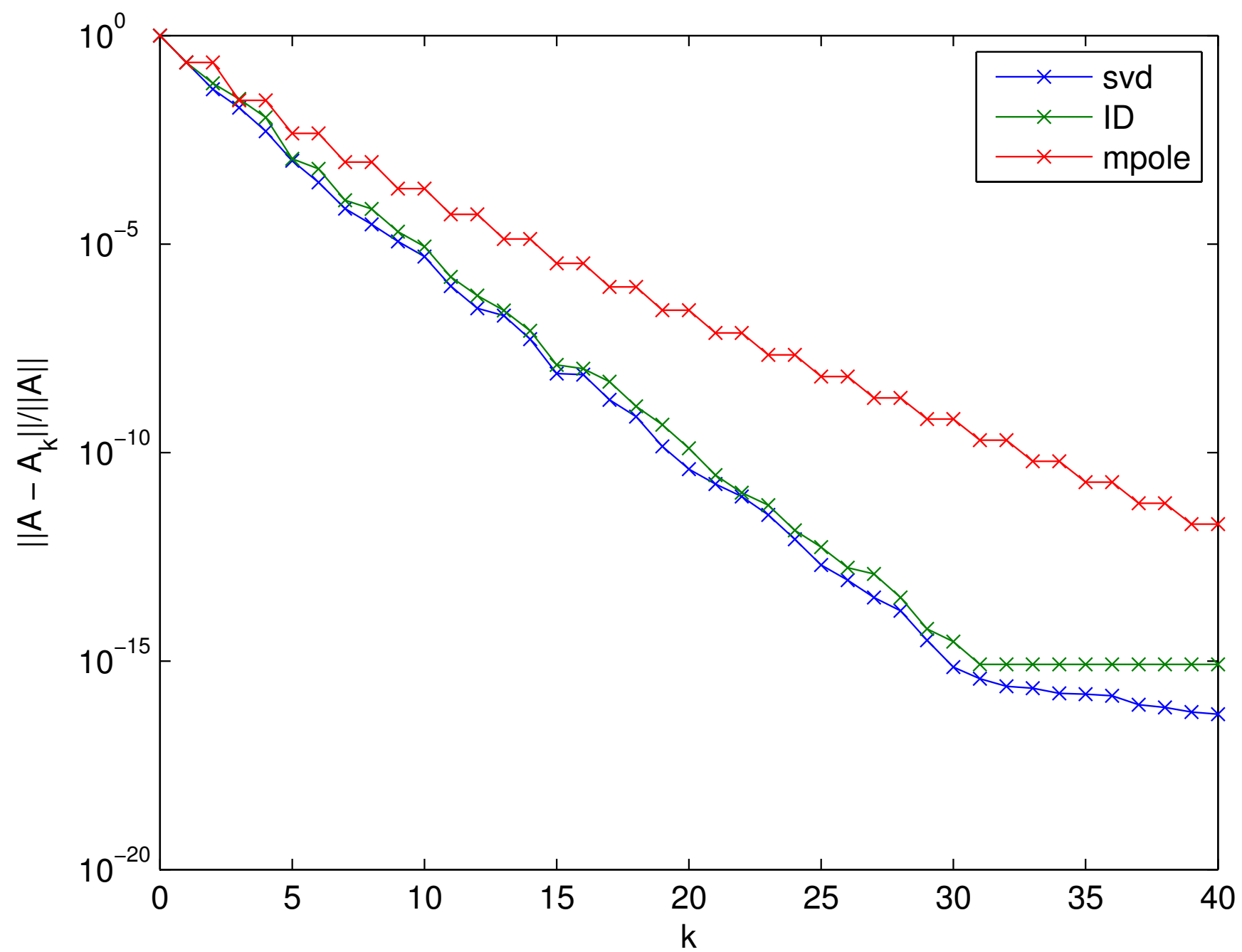


Example: A piece of a contour.

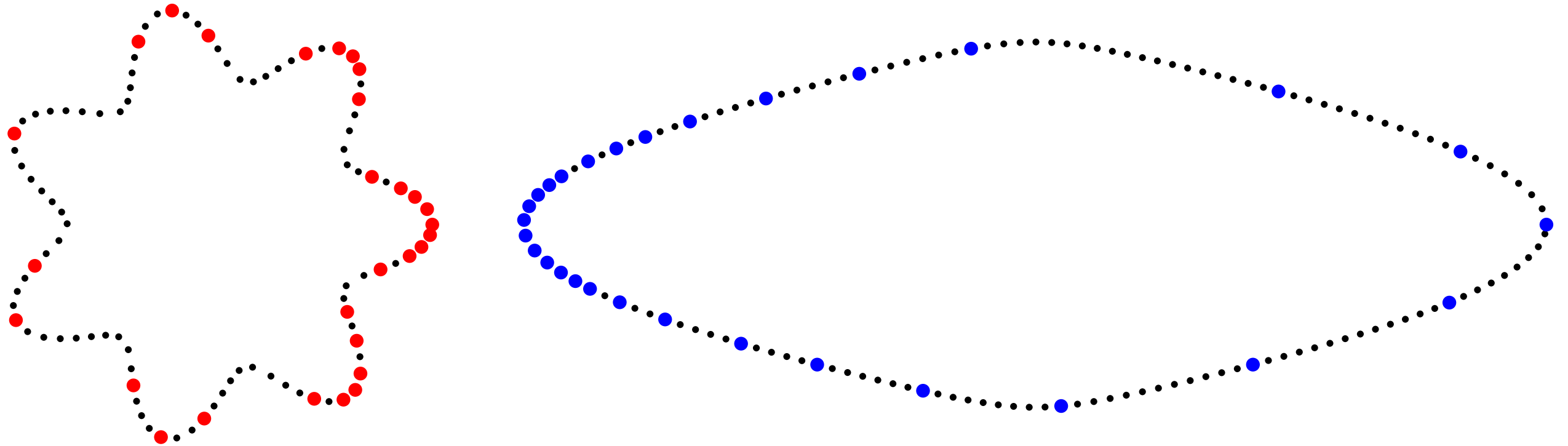


Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 25$.

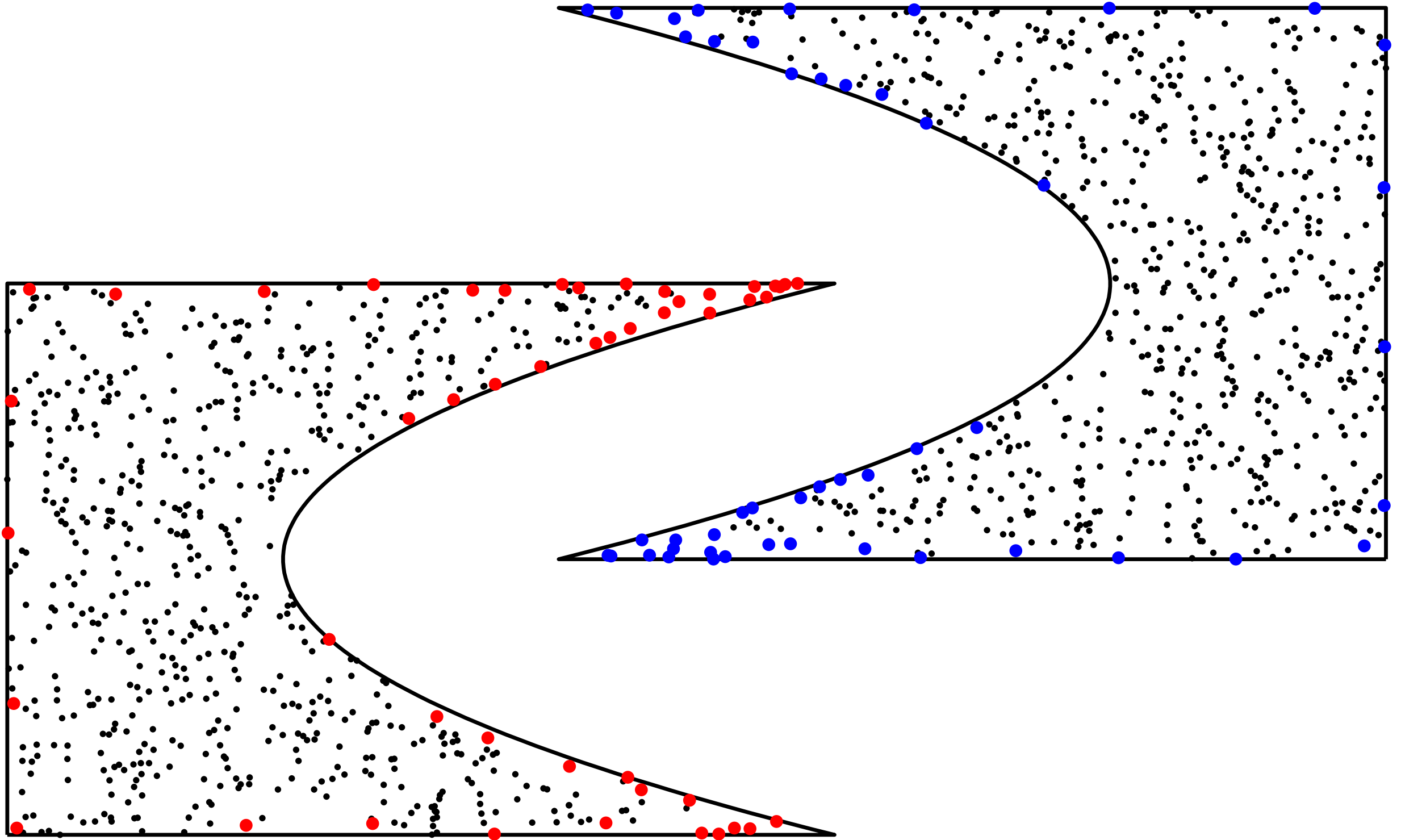
Example: A piece of a contour.



Skeletonization can be performed for Ω_S and Ω_T of various shapes.

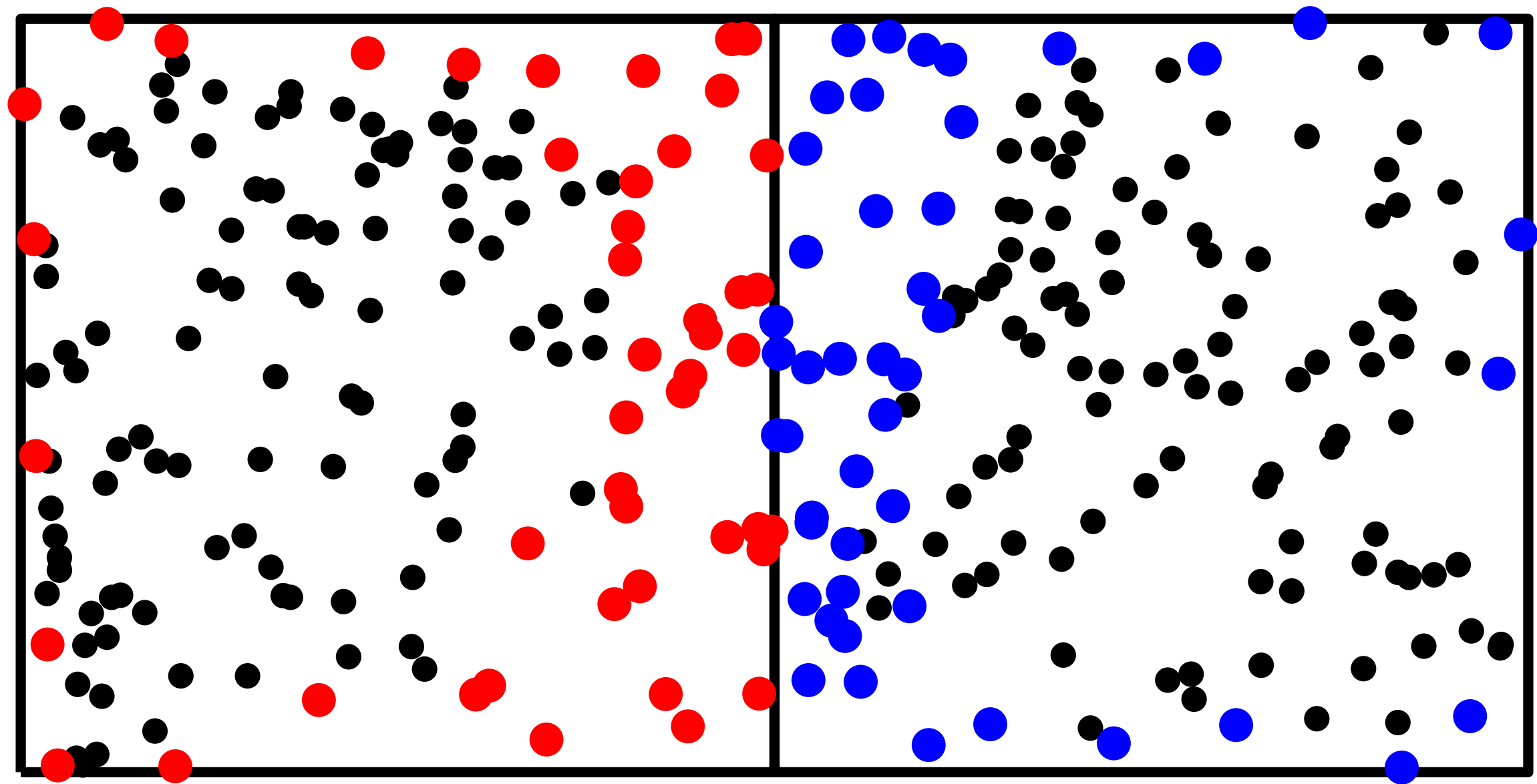


Rank = 29 at $\varepsilon = 10^{-10}$.



Rank = 48 at $\varepsilon = 10^{-10}$.

Adjacent boxes can be skeletonized.



Rank = 46 at $\varepsilon = 10^{-10}$.

$$\begin{array}{ccc}
 \{q_j\}_{j=1}^n & \xrightarrow{\mathbf{A}} & \{u_i\}_{i=1}^m \\
 \downarrow \mathbf{V}^* & & \uparrow \mathbf{U} \\
 \{\hat{q}_p\}_{p=1}^k & \xrightarrow{\mathbf{A}^{\text{skel}}} & \{\hat{u}_p\}_{p=1}^k
 \end{array}$$

Benefits:

- The rank is typically very close to optimal.
- The projection and interpolation are well-conditioned.
- An inexpensive local computation (e.g. Gram-Schmidt) determines:
 - The k skeleton points.
 - Matrices \mathbf{U} and \mathbf{V} .
- The map \mathbf{A}^{skel} has the same kernel as \mathbf{A} .
 (We loosely say that “the physics of the problem is preserved”.)
- The skeleton points can be determined either as generic points valid for any source distribution, or as a subset of a given set of points. In the latter case \mathbf{U} and \mathbf{V} contain $k \times k$ identity matrices.
- Interaction between *adjacent* boxes can be compressed (no buffering is required).

Before closing this topic, let us briefly consider the *Helmholtz problem*.

Recall that the Helmholtz equation is associated with the classical wave equation

$$(2) \quad -v^2 \Delta \phi = -\frac{\partial^2 \phi}{\partial t^2},$$

where v is the wave-speed. Assume $\phi(\mathbf{x}, t) = u(\mathbf{x}) e^{i\omega t}$. Then (2) turns into

$$(3) \quad -v^2 \Delta u = \omega^2 u,$$

We define the “wave number” as $\kappa = \omega/v$, and can then write (3) as

$$(4) \quad -\Delta u - \kappa^2 u = 0.$$

A typical “free-space” problem for the Helmholtz equation could read

$$(5) \quad \begin{cases} -\Delta u(\mathbf{x}) - \kappa^2 u(\mathbf{x}) = q(\mathbf{x}), & \mathbf{x} \in \mathbb{R}^2 \\ \frac{\partial u(\mathbf{x})}{\partial |\mathbf{x}|} - i\kappa u(\mathbf{x}) = O\left(\frac{1}{|\mathbf{x}|}\right) & |\mathbf{x}| \rightarrow \infty, \end{cases}$$

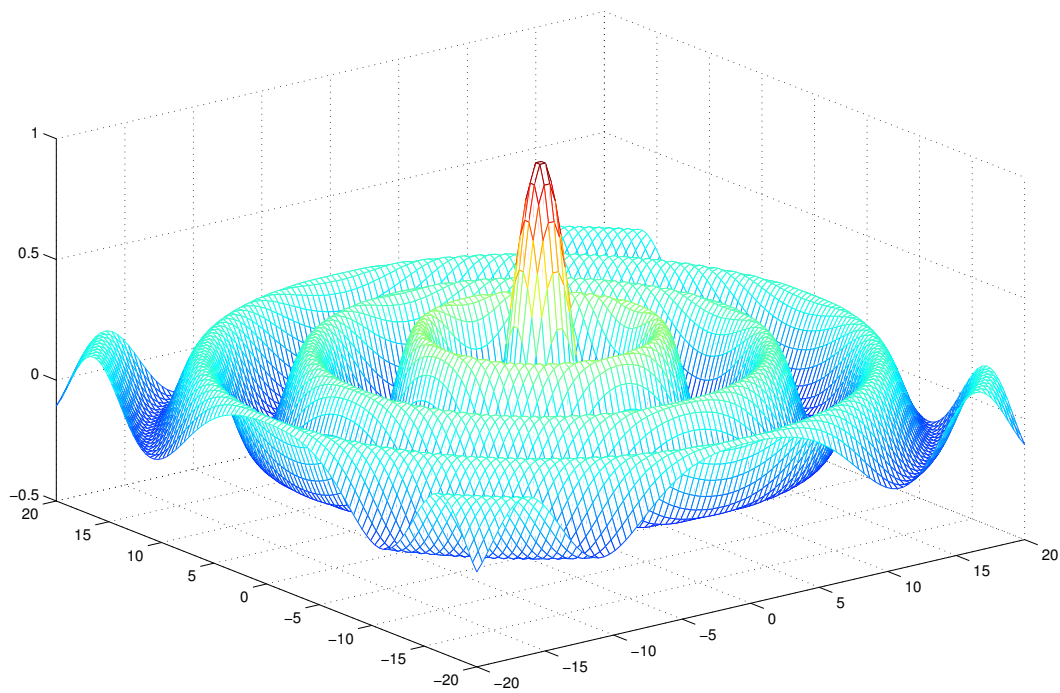
where the condition “at infinity” is called a “radiation condition.”

We typically consider u to be a *complex valued* potential.

The fundamental solution is $H_0^{(1)}(\kappa|\mathbf{x}|)$, so the solution to (5) is

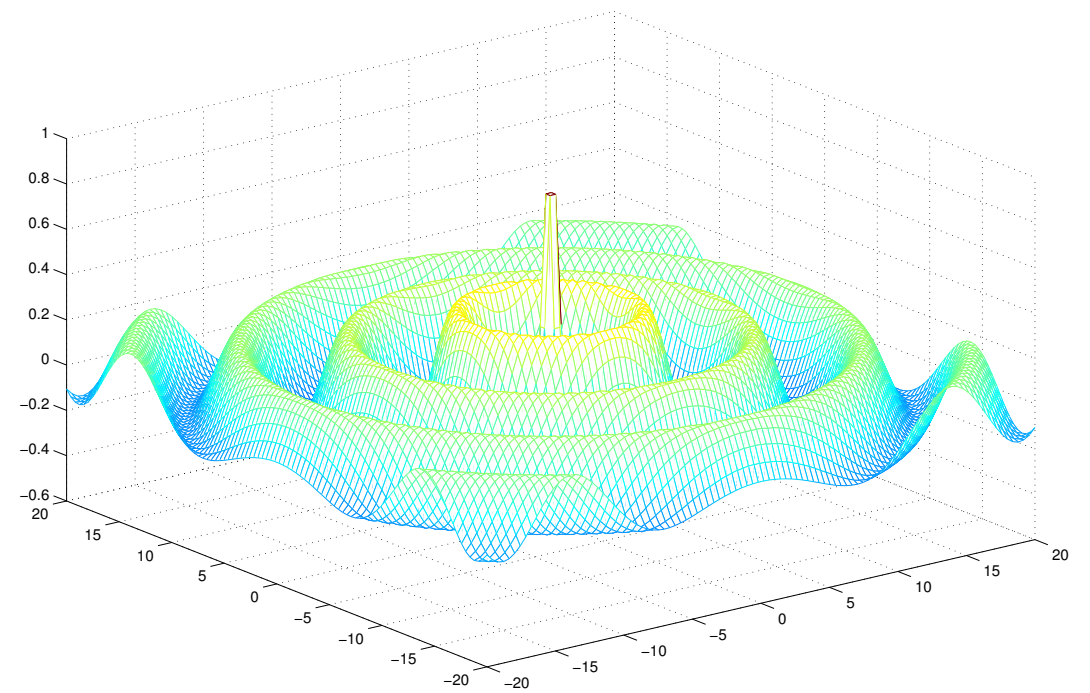
$$u(\mathbf{x}) = \int_{\mathbb{R}^2} H_0^{(1)}(\kappa|\mathbf{x} - \mathbf{y}|) q(\mathbf{y}) d\mathbf{y}.$$

Plots of the fundamental solution $H_0^{(1)}(|\mathbf{x}|) = J_0(|\mathbf{x}|) + i Y_0(|\mathbf{x}|)$.



Real part

J_0

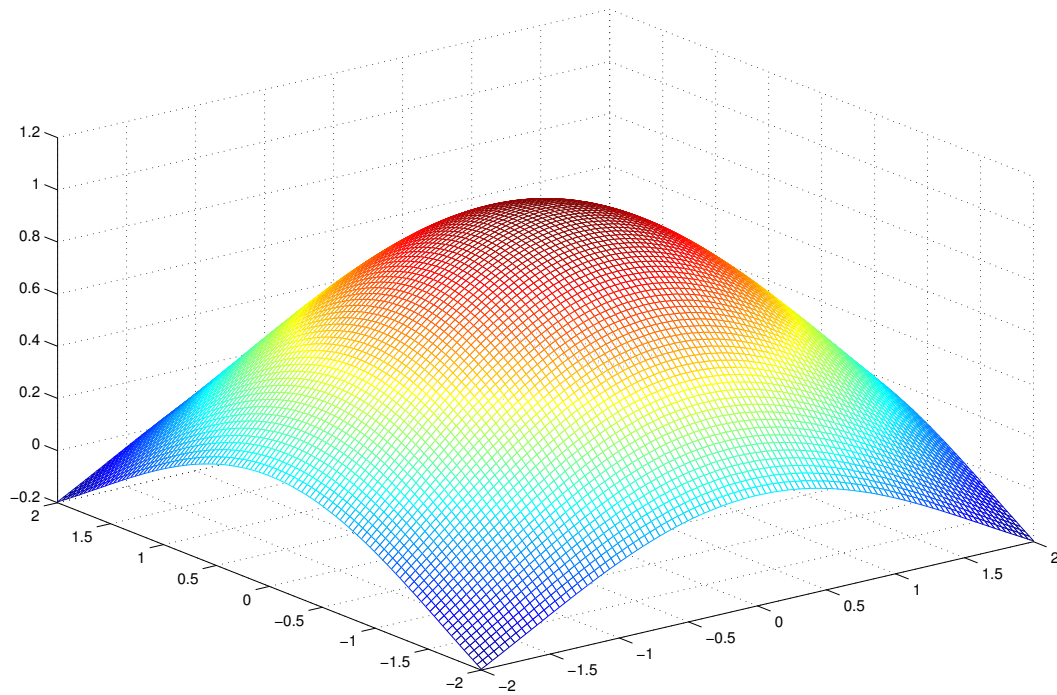


Negative imaginary part

$-Y_0$

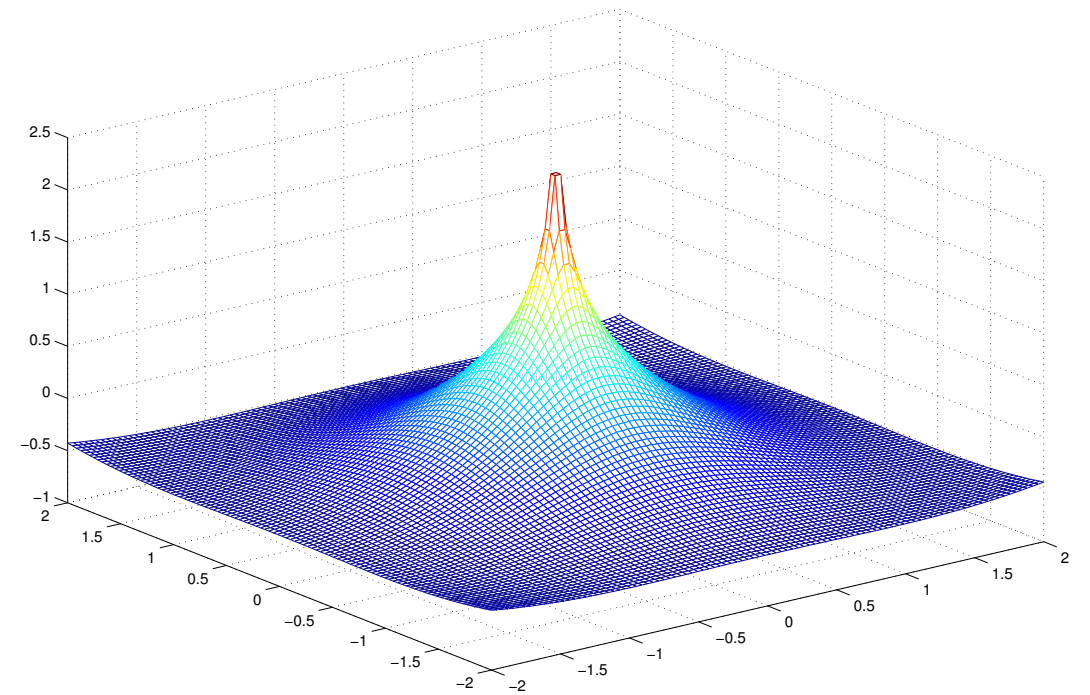
Plots of the fundamental solution $H_0^{(1)}(|\mathbf{x}|) = J_0(|\mathbf{x}|) + i Y_0(|\mathbf{x}|)$.

Now zoom in to the origin:



Real part

J_0



Negative imaginary part

$-Y_0$

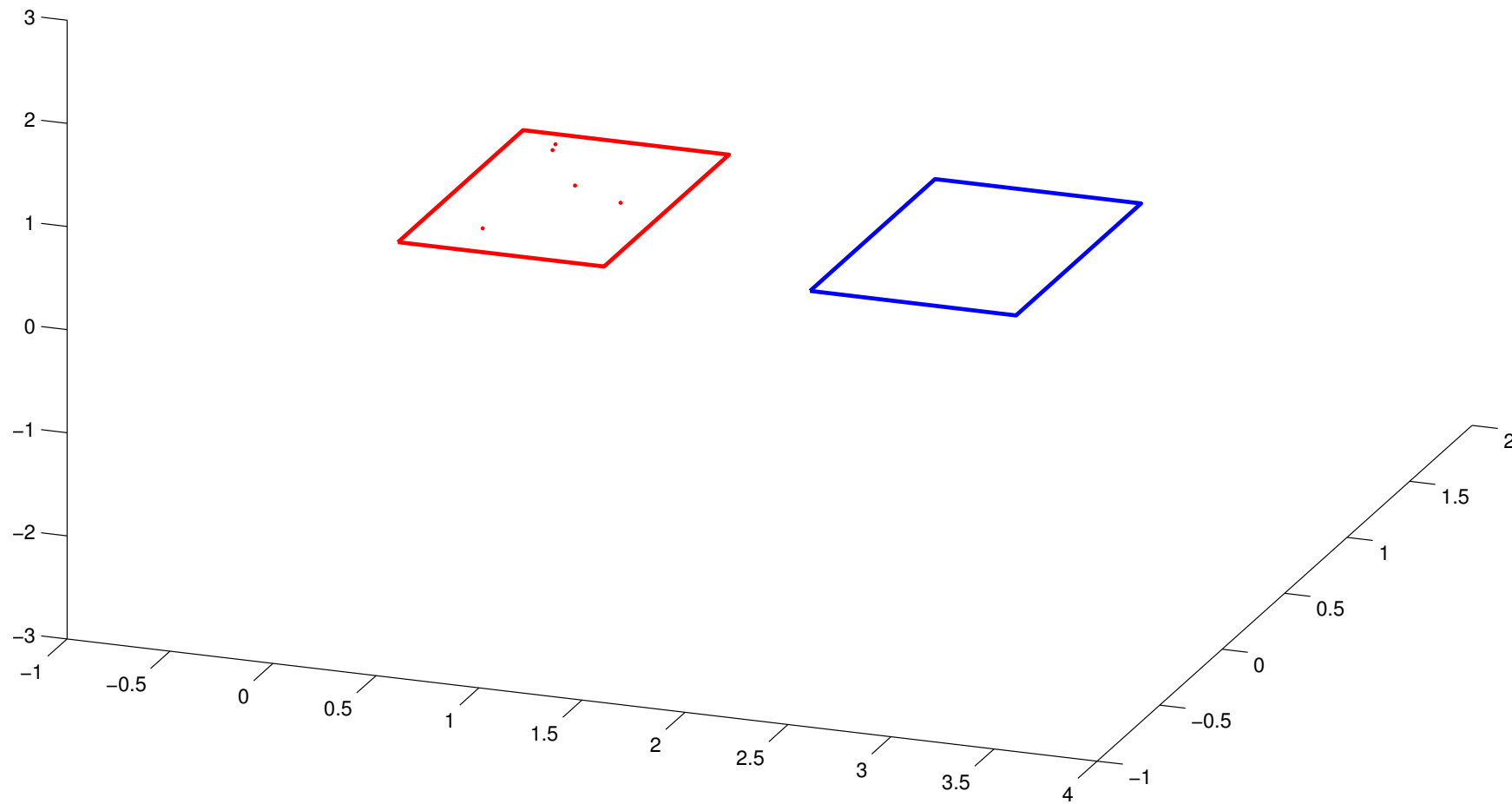
Logarithmic singularity at the origin!

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

We are interested in the potential in a “target domain” Ω_t .

Helmholtz problem. Side of boxes = 0.80 lambda



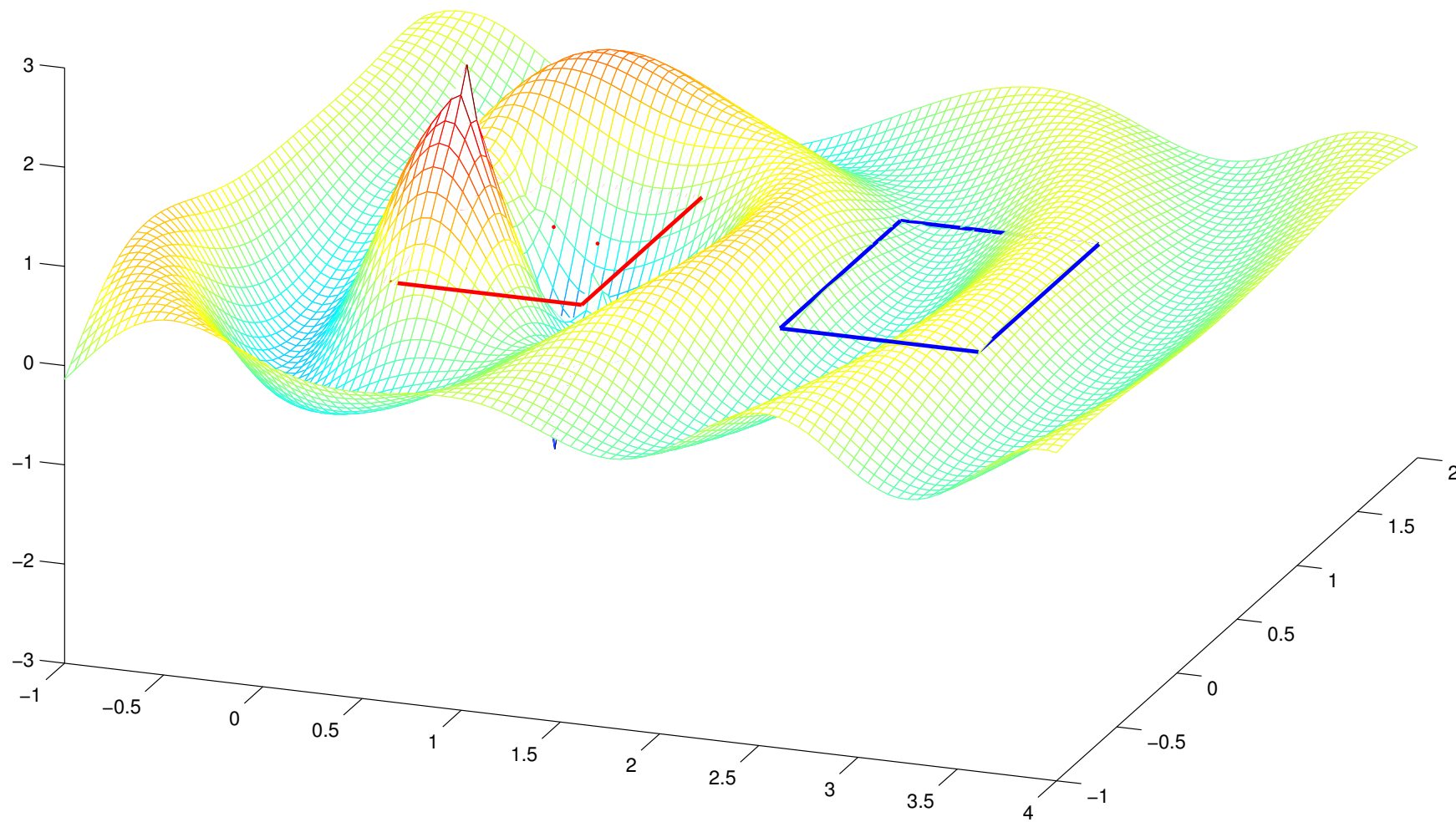
The source domain Ω_S (red) and the target domain Ω_t (blue).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

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Helmholtz problem. Side of boxes = 0.80 lambda



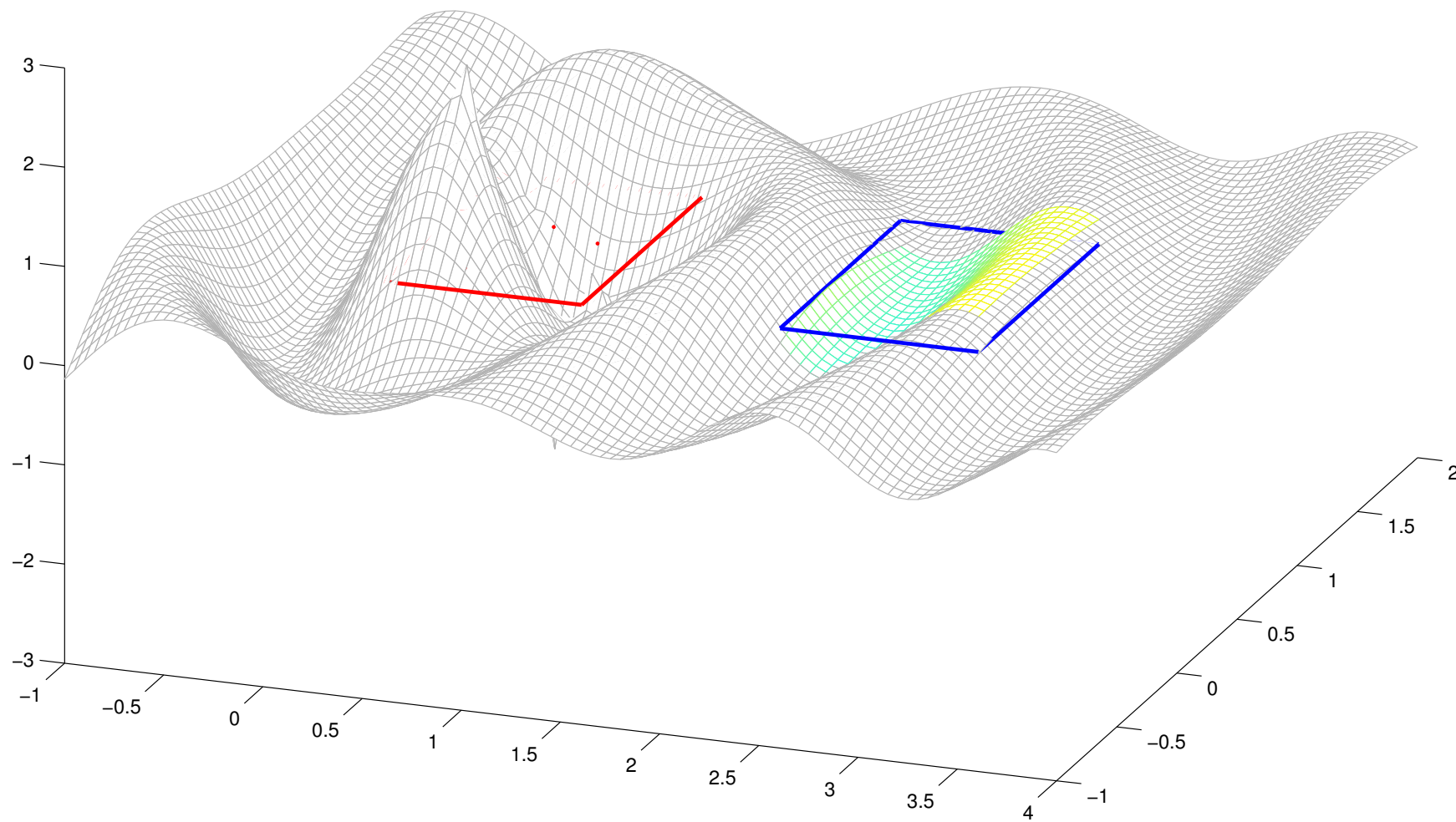
Real part of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

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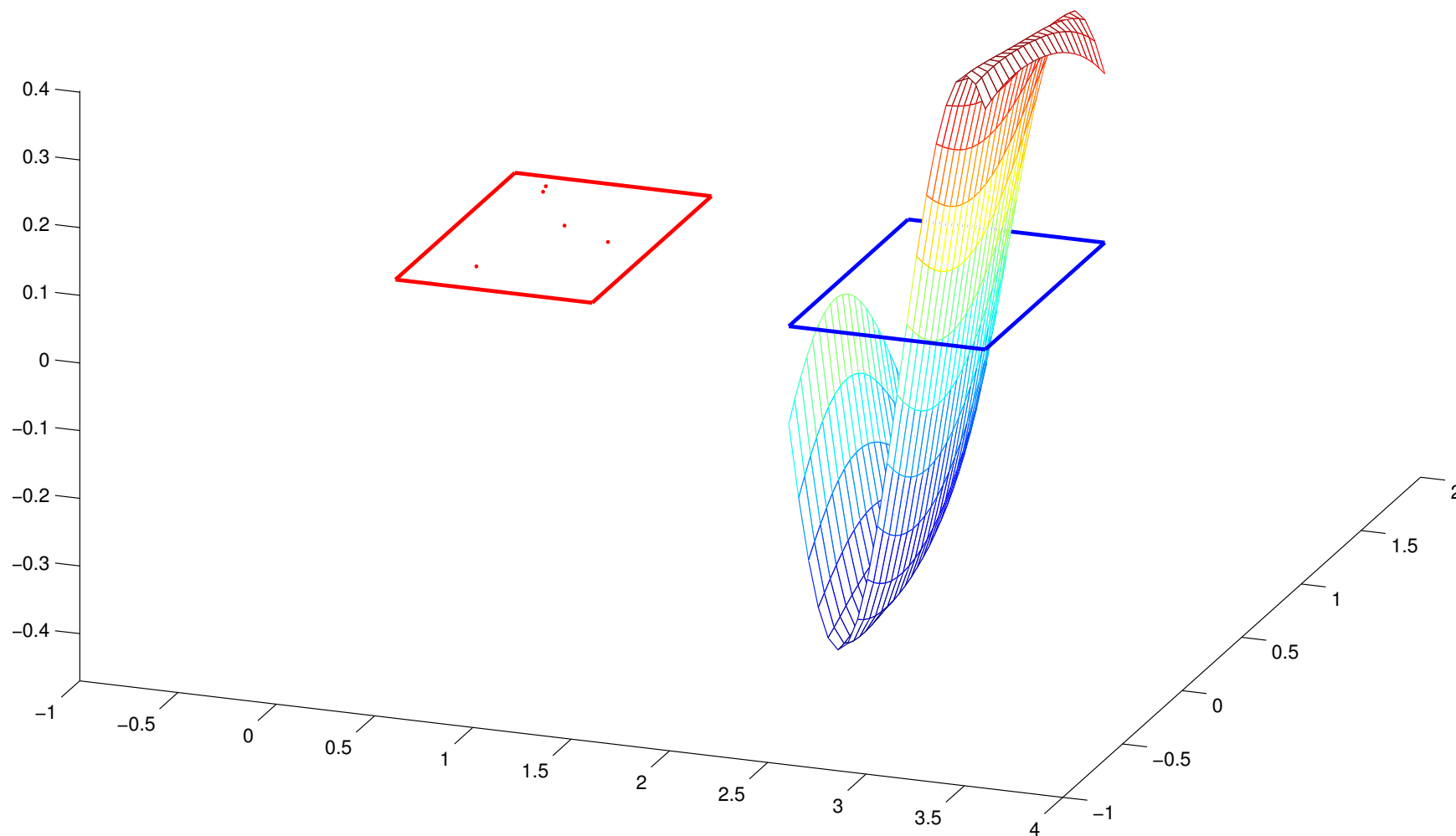
Real part of field generated by the sources (truncated — the peaks go to infinity).

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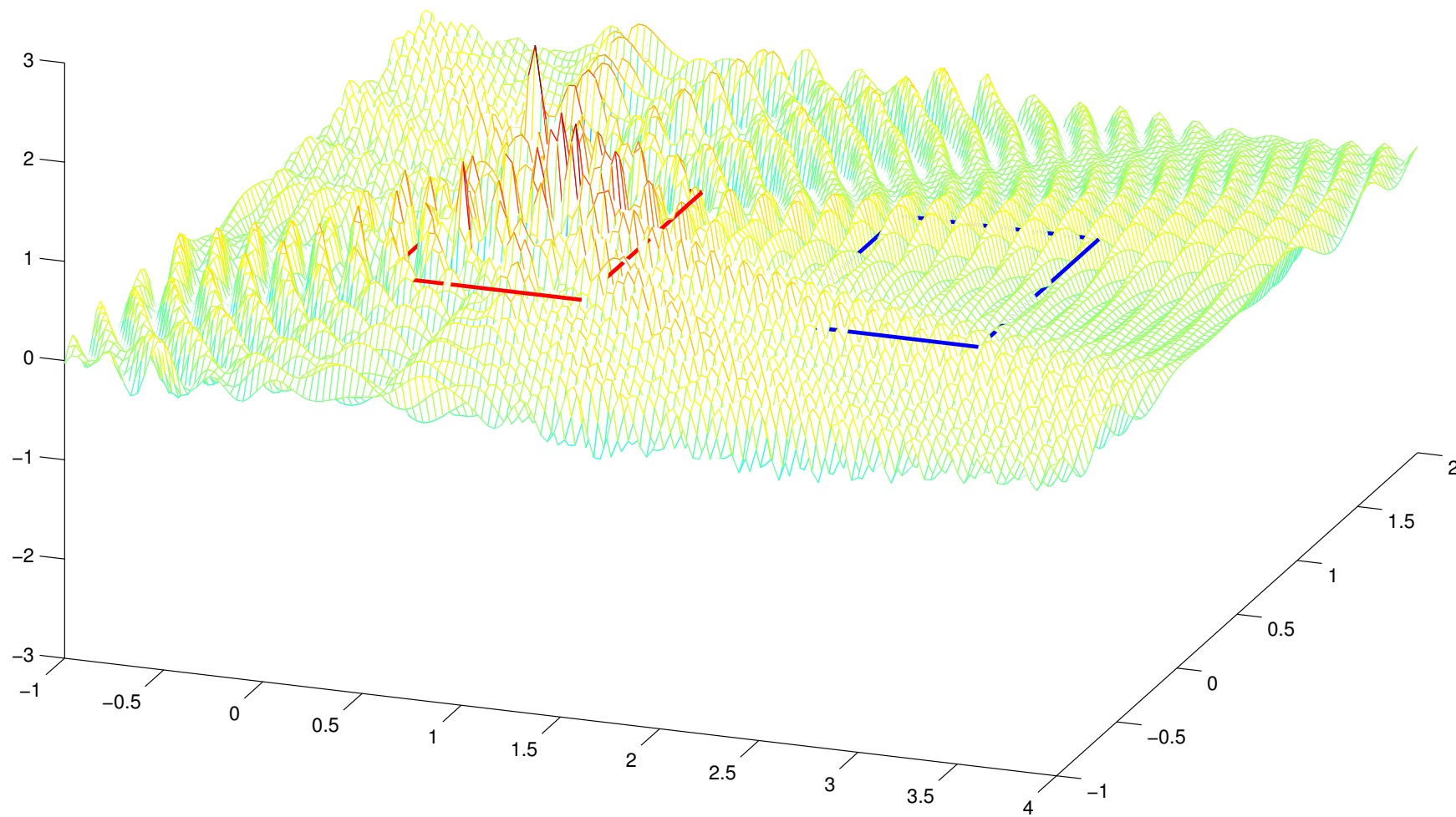
Real part of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

We are interested in the potential in a “target domain” Ω_t . *Now for larger κ !*

Helmholtz problem. Side of boxes = 6.37 lambda



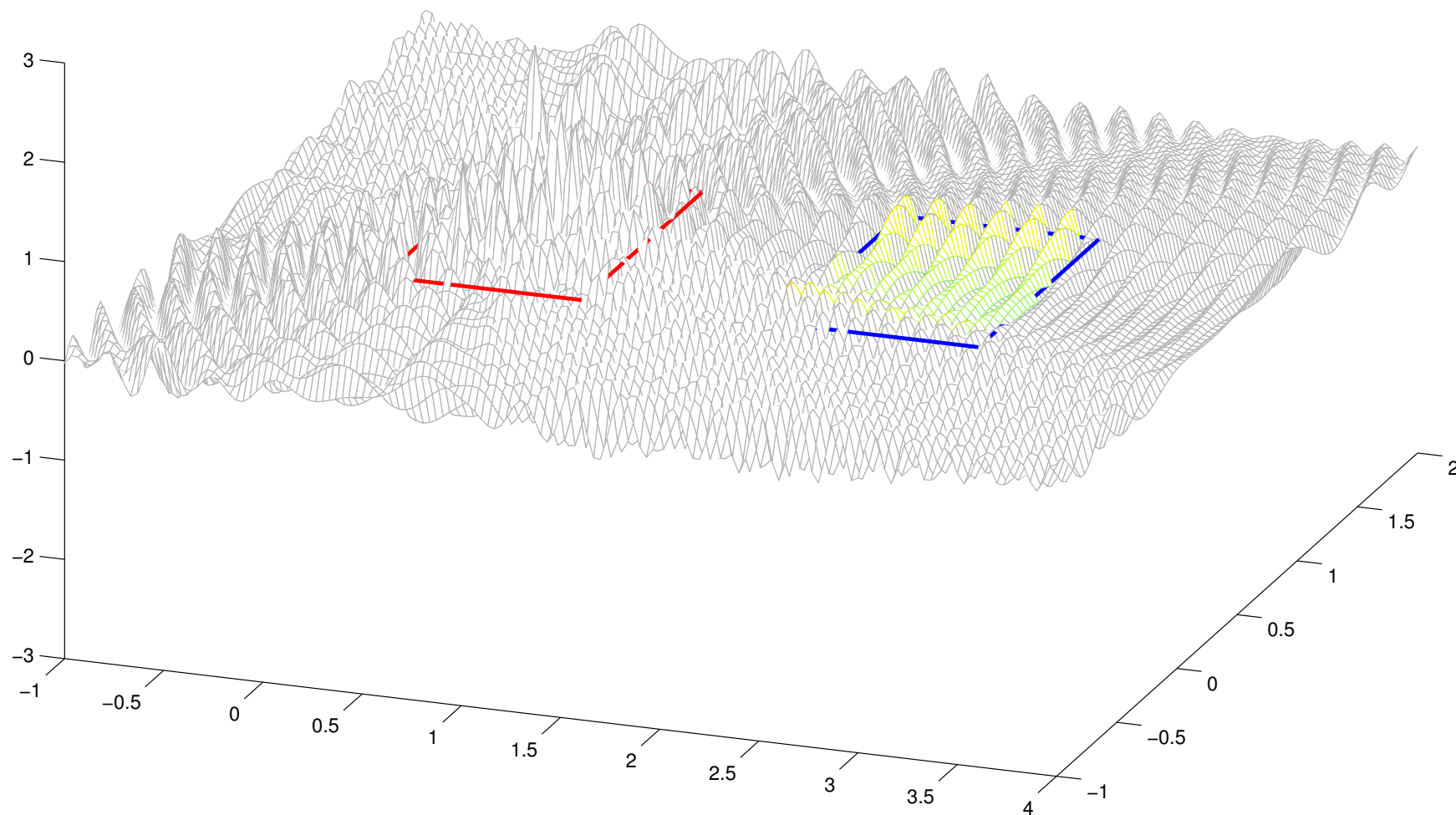
Real part of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

We are interested in the potential in a “target domain” Ω_t . *Now for larger κ !*

Helmholtz problem. Side of boxes = 6.37 lambda



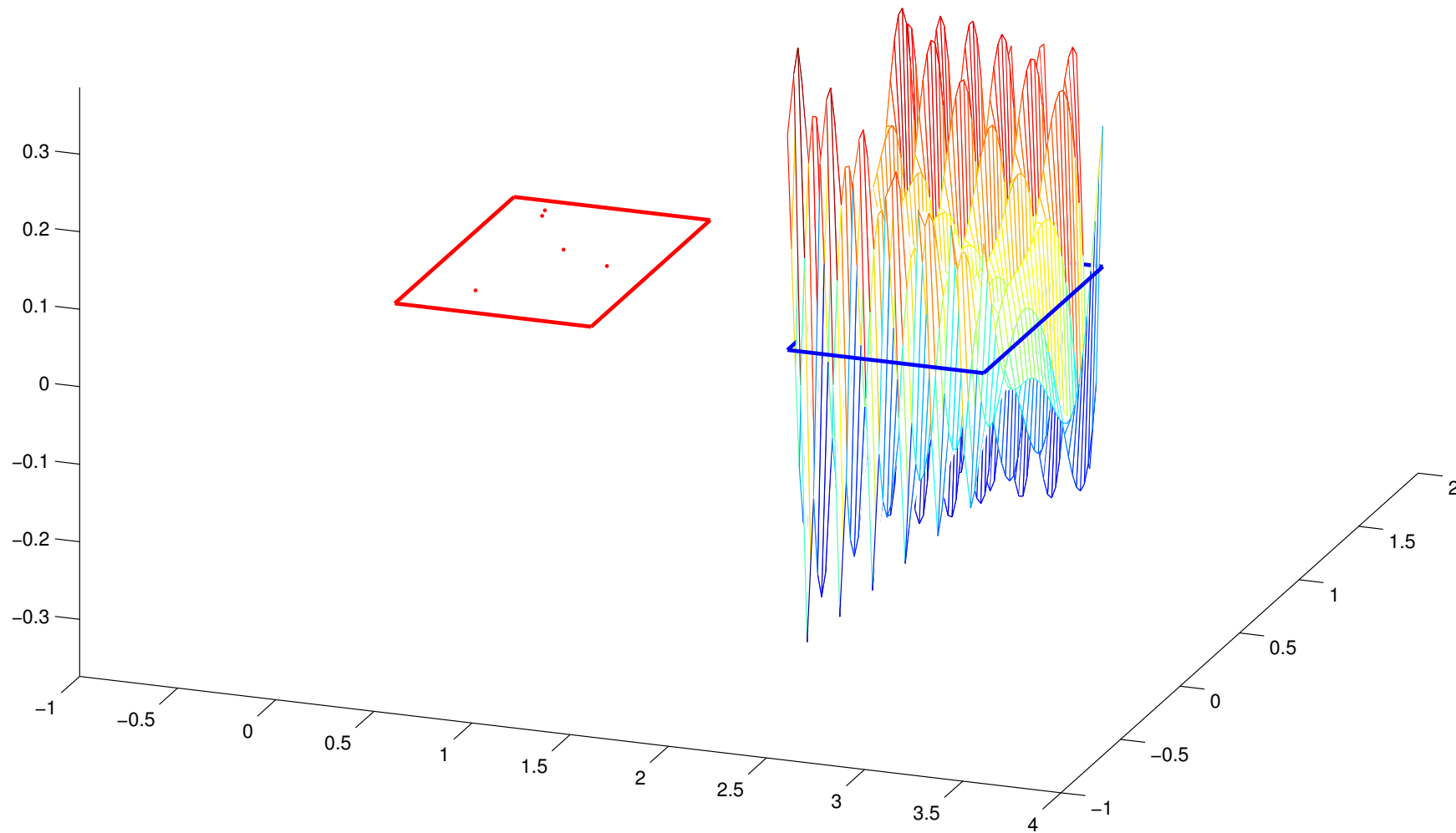
Real part of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

We are interested in the potential in a “target domain” Ω_t . *Now for larger κ !*

Helmholtz problem. Side of boxes = 6.37 lambda



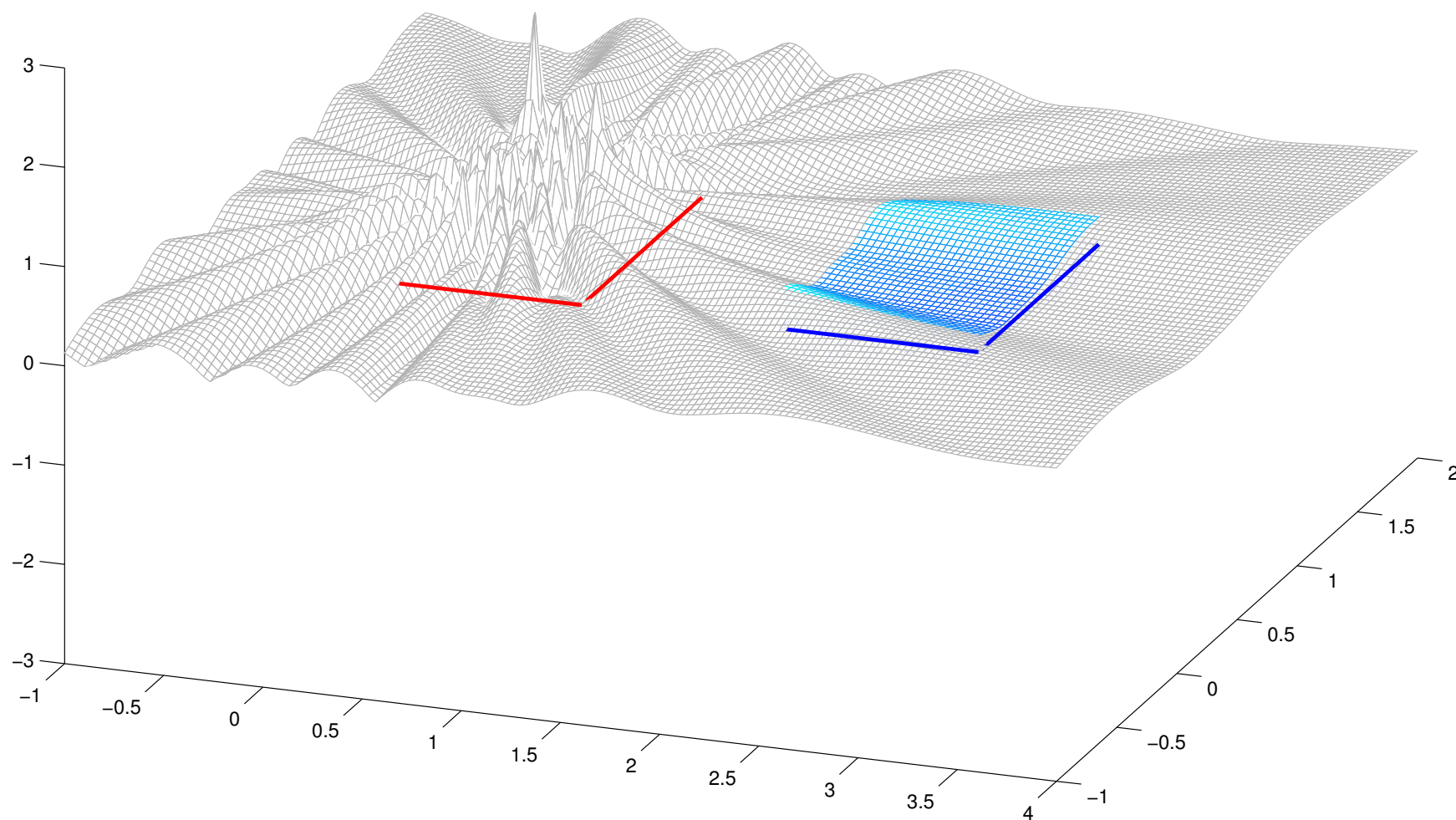
Real part of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

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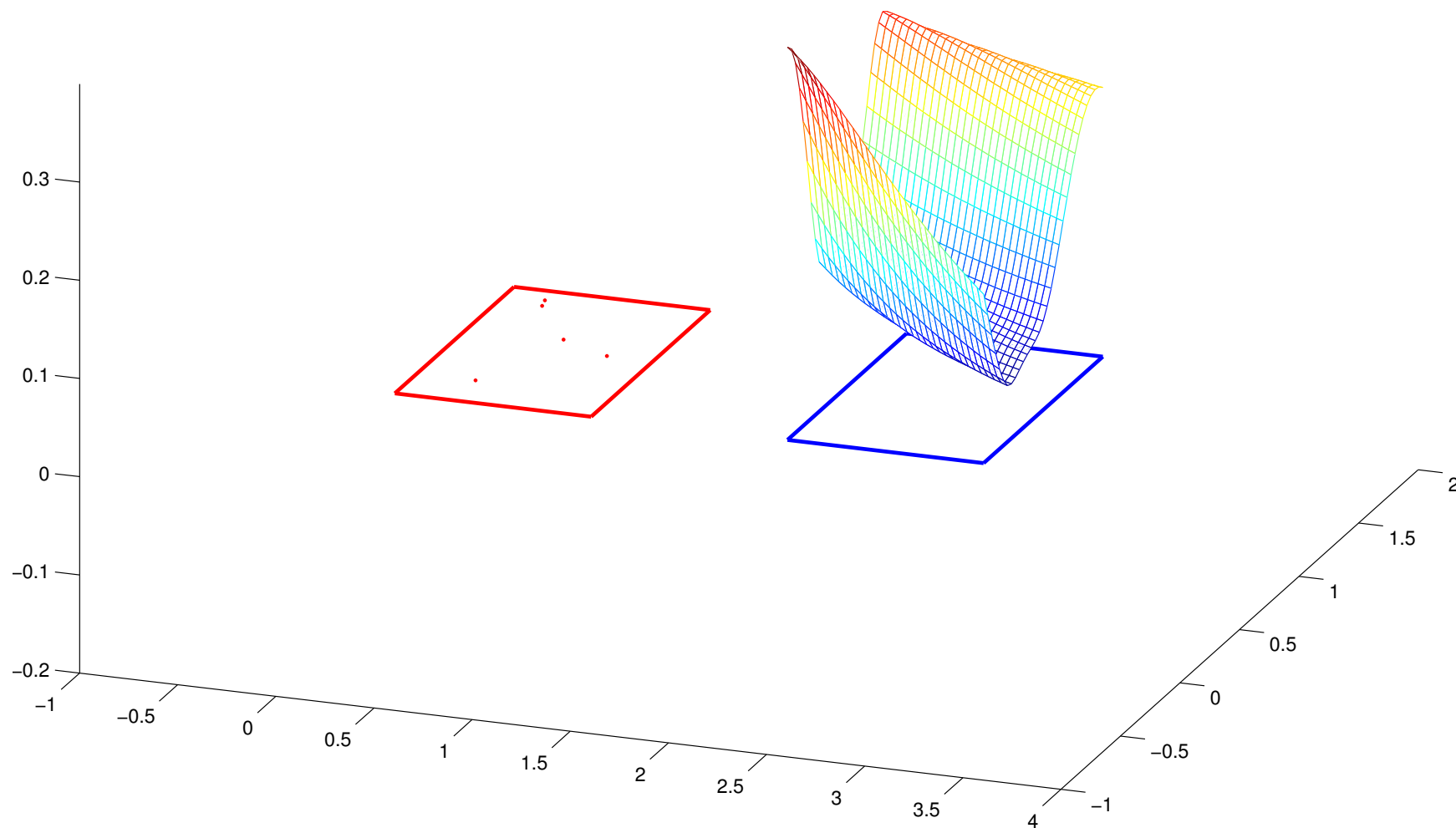
Absolute value of field generated by the sources (truncated — the peaks go to infinity).

Example of solution of the Helmholtz equation $-\Delta u - \kappa^2 u = g$

Suppose we are given point charges $\{q_j\}_{j=1}^5$ in a “source domain” Ω_S .

We are interested in the potential in a “target domain” Ω_t . *Now for larger κ !*

Helmholtz problem. Side of boxes = 6.37 lambda



Absolute value of field generated by the sources (truncated — the peaks go to infinity).

Superficially, almost everything we've discussed for the Laplace case carries right over to the Helmholtz case.

For instance, there is a "multipole expansion." Set

$$S_n(\mathbf{x}) = H_n^{(1)}(\kappa r) e^{-in\theta}$$

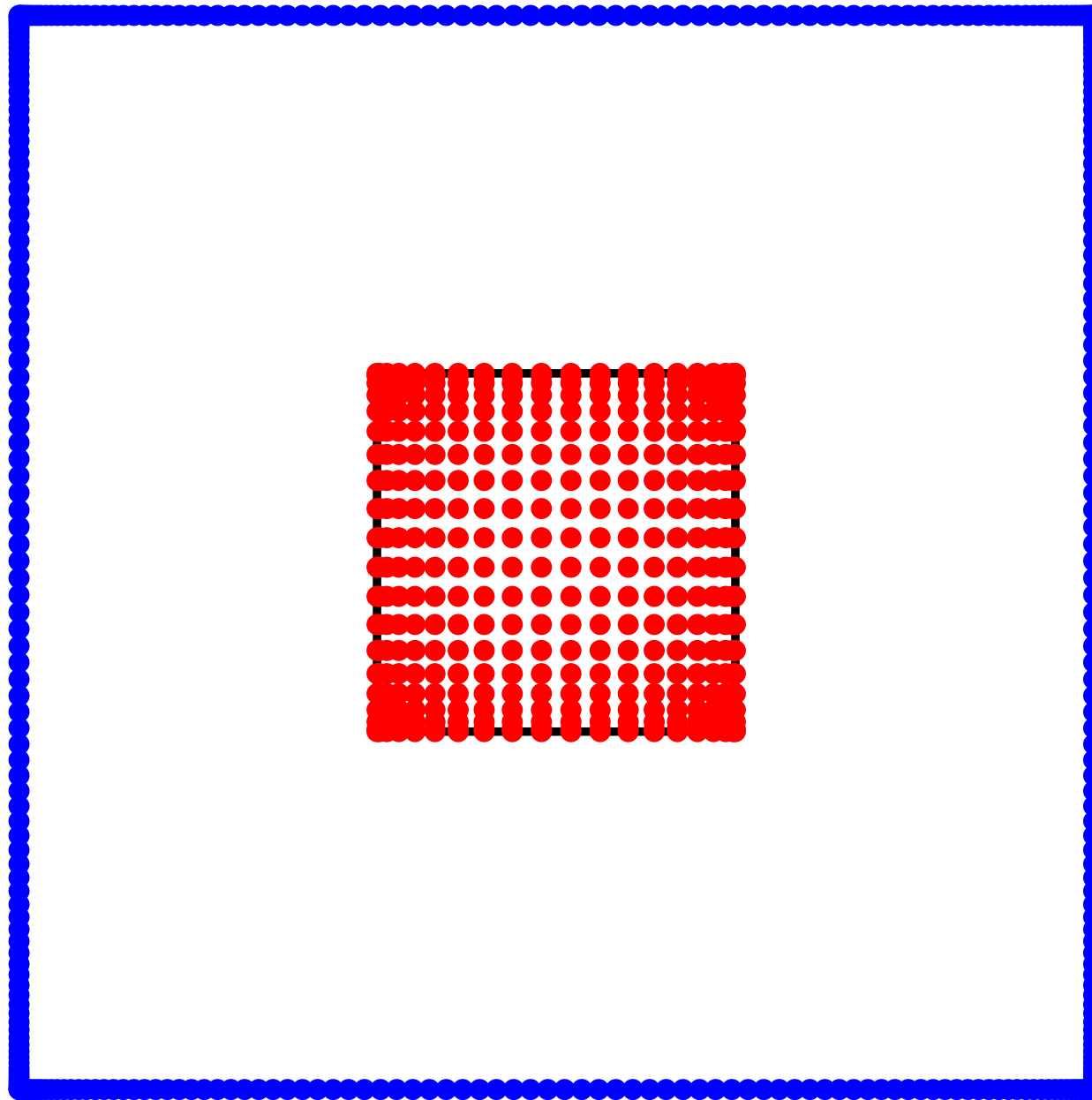
$$R_n(\mathbf{x}) = J_n(\kappa r) e^{in\theta}.$$

Then

$$H_0^{(1)}(\kappa|\mathbf{x} - \mathbf{y}|) = \sum_{n=-\infty}^{\infty} S_n(\mathbf{x}) R_n(\mathbf{y}), \quad \text{when } |\mathbf{x}| > |\mathbf{y}|.$$

Example: Two squares — Helmholtz — small wave number.

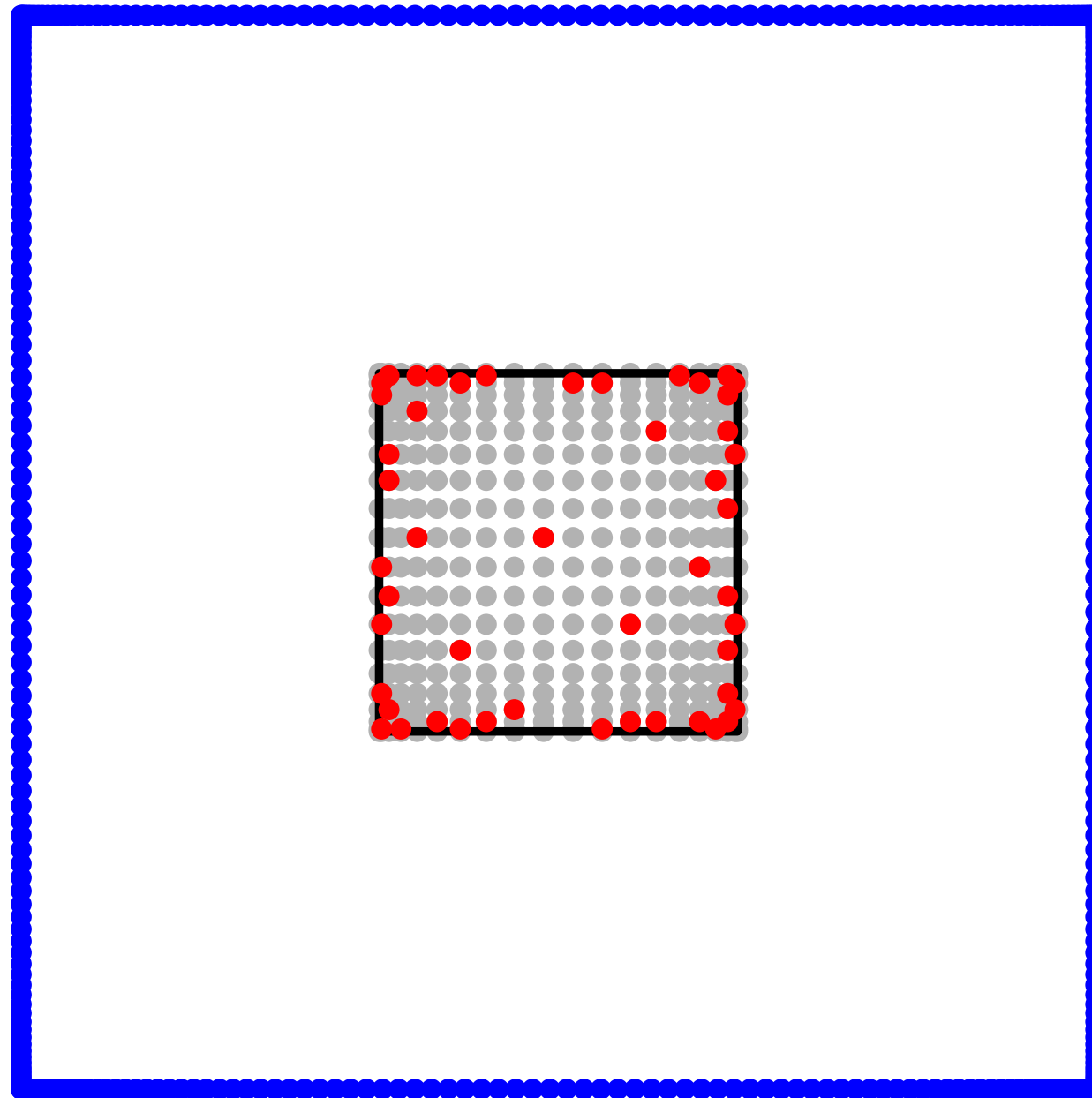
The geometry: Source region has side = 0.875λ



Sources in a box of side length 0.9λ , targets on a box of side length 2.6λ .

Example: Two squares — Helmholtz — small wave number.

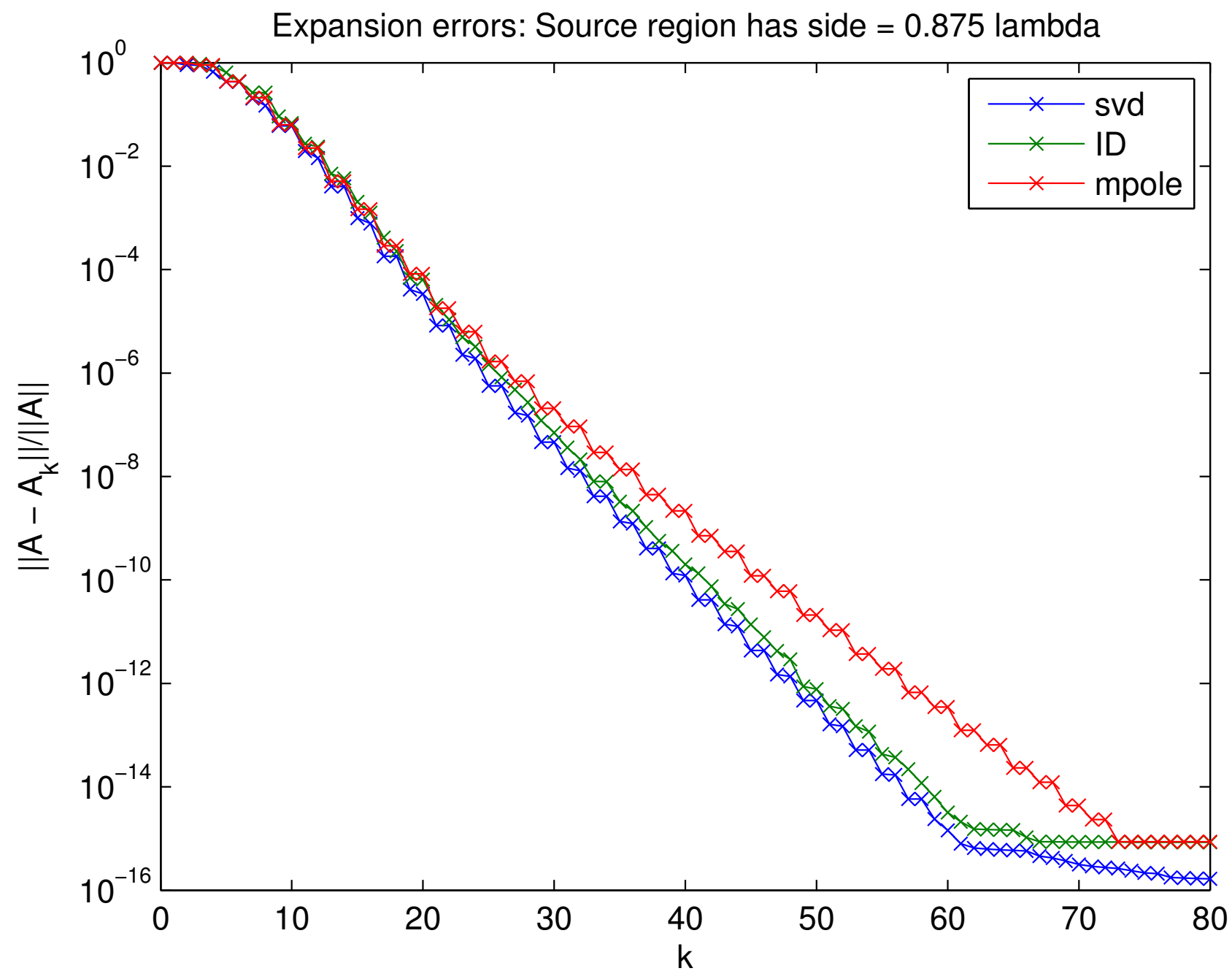
Skeleton points: $\text{eps}=1.0\text{e-}12$ $k=49$ side of source box = 0.875 lambda



Sources in a box of side length 0.9λ , targets on a box of side length 2.6λ .

Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 49$.

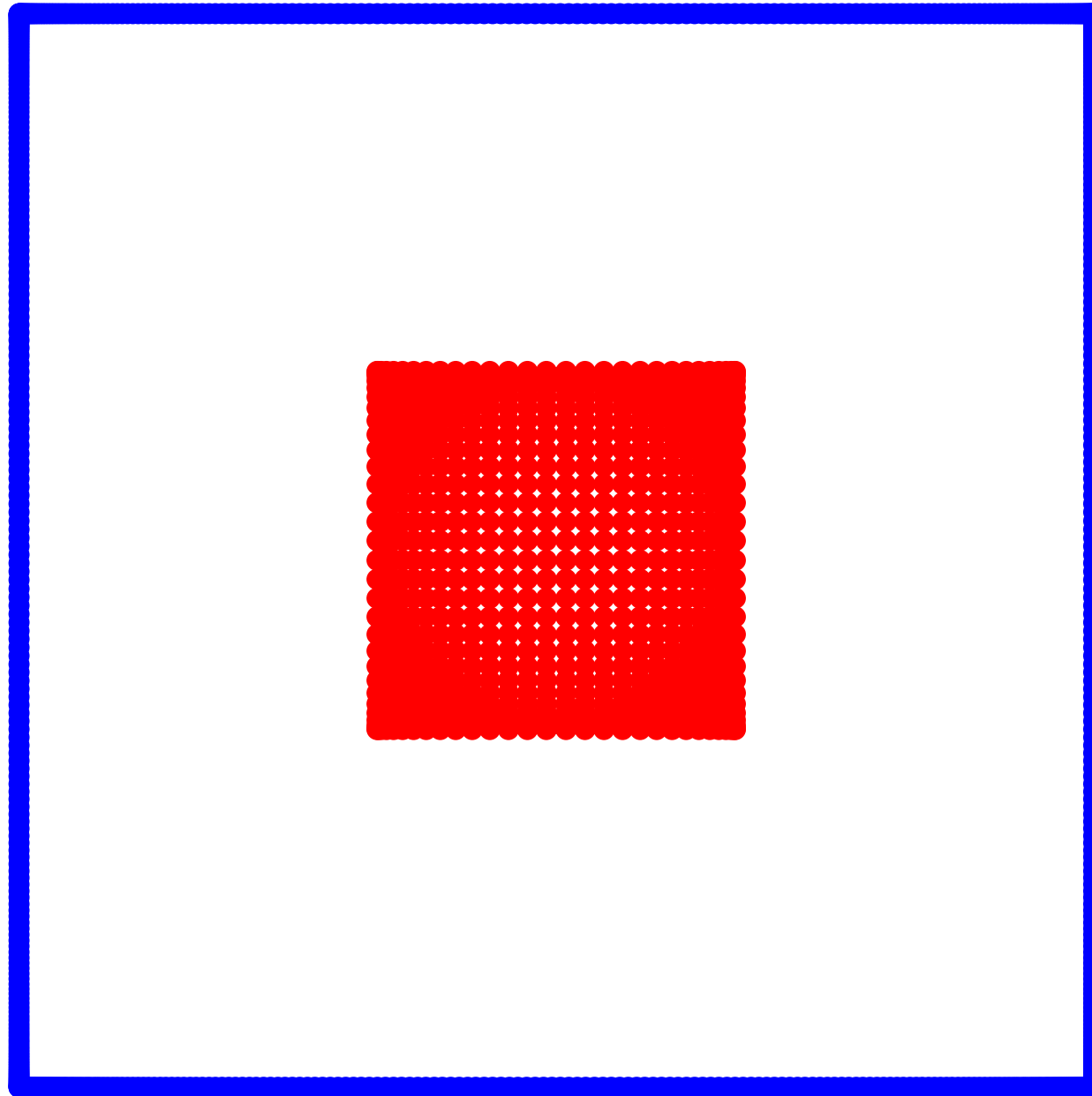
Example: Two squares — Helmholtz — small wave number.



Sources in a box of side length 0.9λ , targets on a box of side length 2.6λ .

Example: Two squares — Helmholtz — medium wave number.

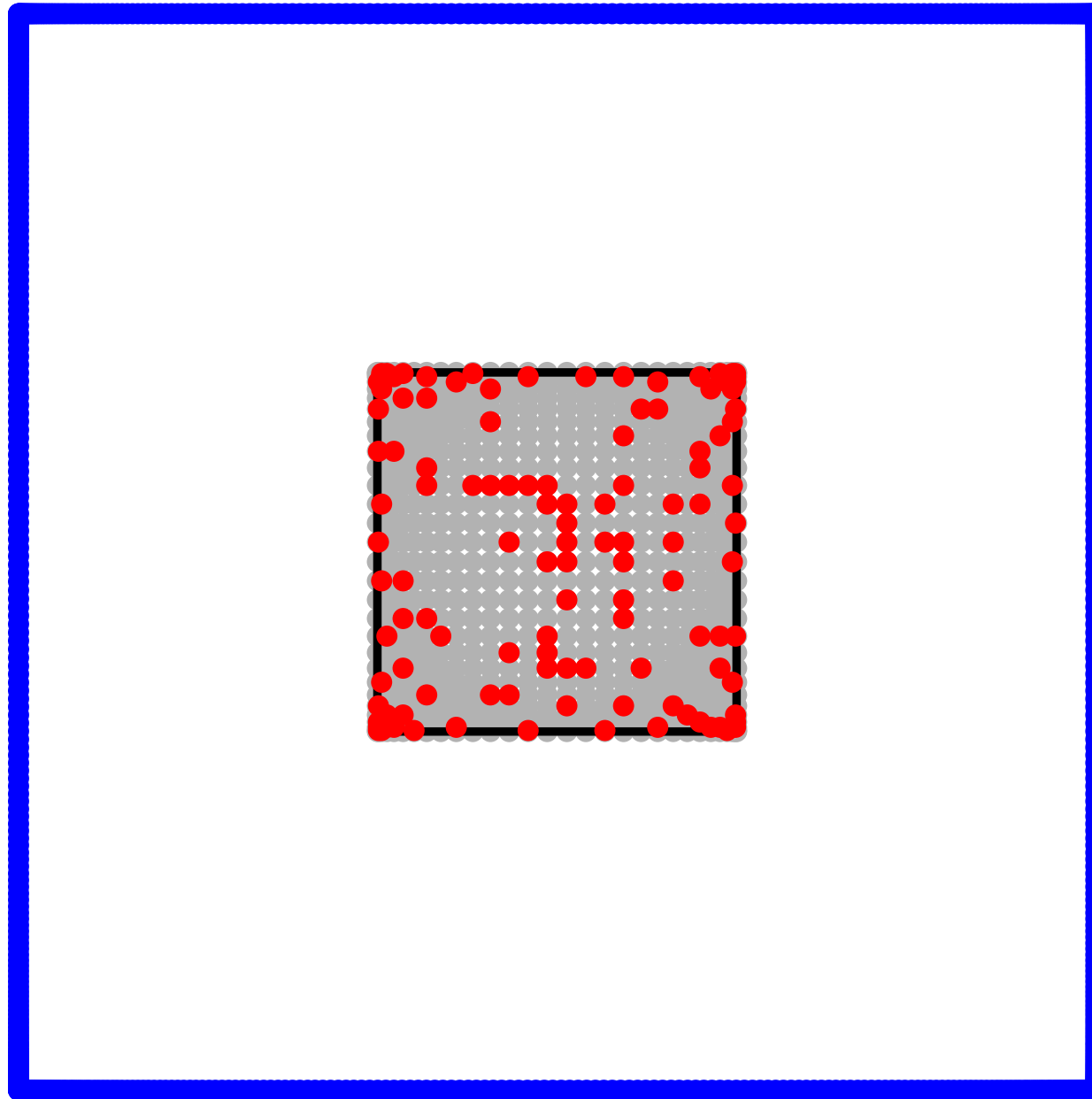
The geometry: Source region has side = 8.117λ



Sources in a box of side length 8.1λ , targets on a box of side length 24.4λ .

Example: Two squares — Helmholtz — medium wave number.

Skeleton points: $\text{eps}=1.0\text{e}-12$ $k=118$ side of source box = 8.117 lambda

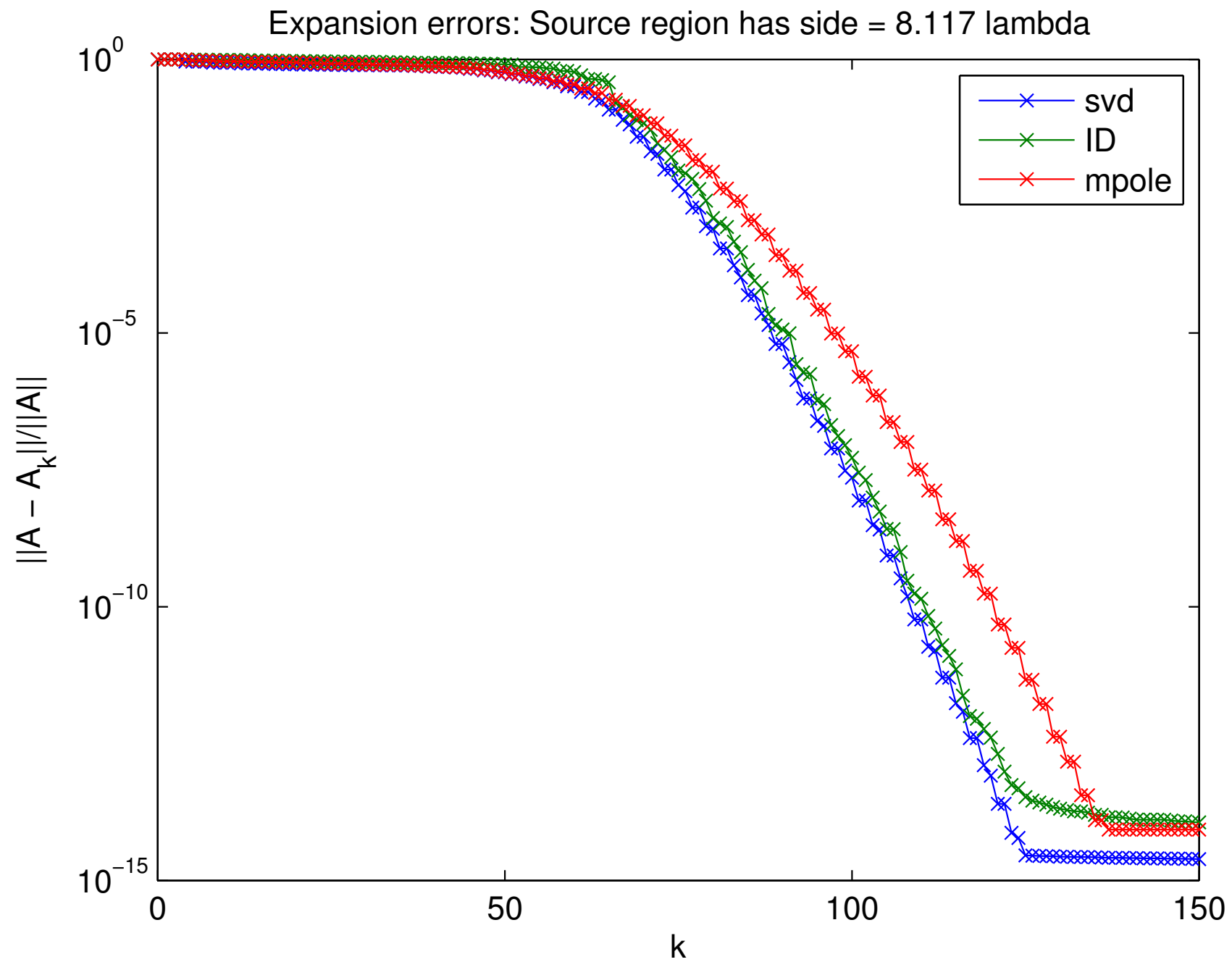


Sources in a box of side length 8.1λ , targets on a box of side length 24.4λ .

Skeleton to precision $\varepsilon = 10^{-12}$, which requires $k = 118$.

Observe how many points are now internal — they used to cluster along the boundary.

Example: Two squares — Helmholtz — medium wave number.



Sources in a box of side length 8.1λ , targets on a box of side length 24.4λ .

Complications with the Helmholtz problem:

1. Decay of singular values starts happening only for *sub-wave-length scales*.

For geometries that are “large” in terms of wave-lengths, rank considerations alone will be not be sufficient.

2. Resonances are possible. Consider for instance the Dirichlet boundary value problem:

$$\begin{cases} -\Delta u(\mathbf{x}) - \kappa^2 u(\mathbf{x}) = 0, & \mathbf{x} \in \Omega, \\ u(\mathbf{x}) = f(\mathbf{x}), & \mathbf{x} \in \partial\Omega, \end{cases}$$

where Ω is a “simple” finite domain. There exist a sequence of wave-numbers $0 \leq \kappa_1 \leq \kappa_2 \leq \kappa_3 \leq \dots$ for which the BVP is ill-posed. These are the numbers for which κ_j^2 is an eigenvalue of $-\Delta$. At these “resonant wave-numbers” there exist non-trivial solutions for $f = 0$.

This creates complications in setting up proxy charges (need *two* layers, or use both monopoles and dipoles, e.g.).

3. While the Laplace equation has a simple “maximum principle” (a harmonic function attains its max on the boundary), the Helmholtz equation is more complicated.
4. Etc.

Similar schemes have been proposed by many researchers:

1993 - C.R. Anderson

1995 - C.L. Berman

1996 - E. Michielssen, A. Boag

1999 - J. Makino

2004 - L. Ying, G. Biros, D. Zorin

A mathematical foundation:

1996 - M. Gu, S. Eisenstat