

Randomized SVD for Hilbert-Schmidt operators low-rank approximation

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The problem:

Low rank approximation for the kernel function $G(x, y)$ of an integral Hilbert-Schmidt operator \mathcal{F} :

$$(\mathcal{F} f)(x) = \int_D G(x, y) f(y) \, dy, \quad x \in D, \quad f \in L^2(D)$$

Applications:

1. Learning integral kernels such as Green functions associated with linear partial differential equations
2. Compressed storage of Integral operators
3. Fast Integral operators evaluation

Recently proposed solution

Published as a conference paper at ICLR 2022

A GENERALIZATION OF THE RANDOMIZED SINGULAR VALUE DECOMPOSITION

Nicolas Boullé

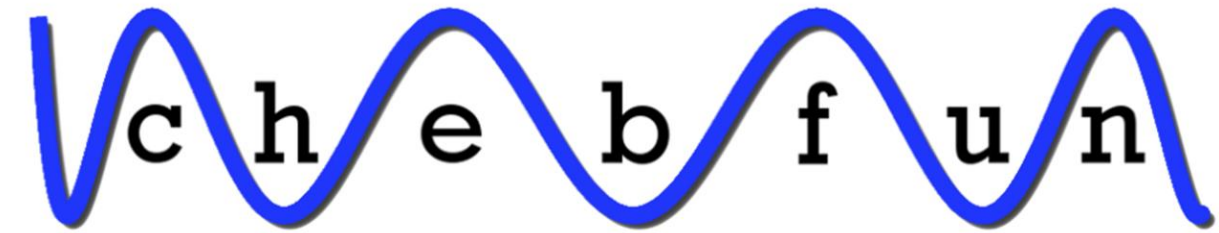
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The article proposes an algorithm for the generalization of randomized SVD for Hilbert-Schmidt operators with non-standard covariance kernels.

The algorithm



Algorithm 1 Randomized SVD for HS operators

Input: HS integral operator \mathcal{F} with kernel $G(x, y)$, number of samples $k > 0$

Output: Approximation G_k of G

- 1: Define a GP covariance kernel K
 - 2: Sample the GP k times to generate a quasimatrix of random functions $\Omega = [f_1 \dots f_k]$
 - 3: Evaluate the integral operator at Ω , $Y = [\mathcal{F}(f_1) \dots \mathcal{F}(f_k)]$
 - 4: Orthonormalize the columns of Y , $Q = \text{orth}(Y) = [q_1 \dots q_k]$
 - 5: Compute an approximation to G by evaluating the adjoint of \mathcal{F}
 - 6: Initialize $G_k(x, y)$ to 0
 - 7: **for** $i = 1 : k$ **do**
 - 8: $G_k(x, y) \leftarrow G_k(x, y) + q_i(x) \int_D G(z, y) q_i(z) \mathrm{d}z$ // $G_k = Q(G^*Q)^*$
 - 9: **end for**
-

Experiments: original kernels vs obtained approximations

Kernel

Trigonometric

Airy

Bessel

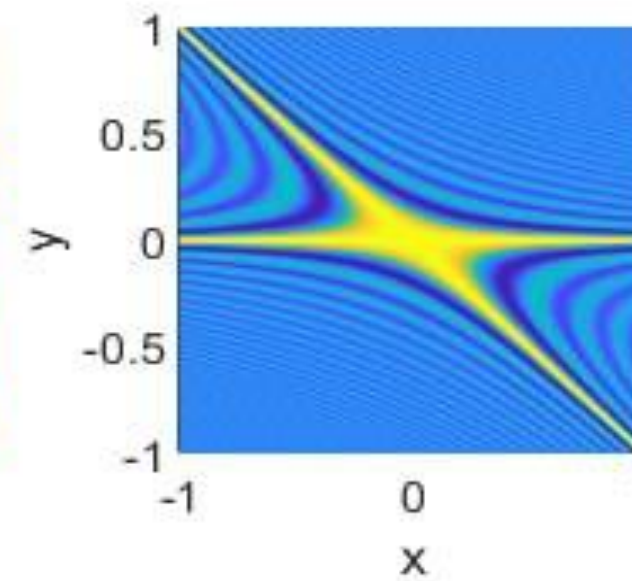
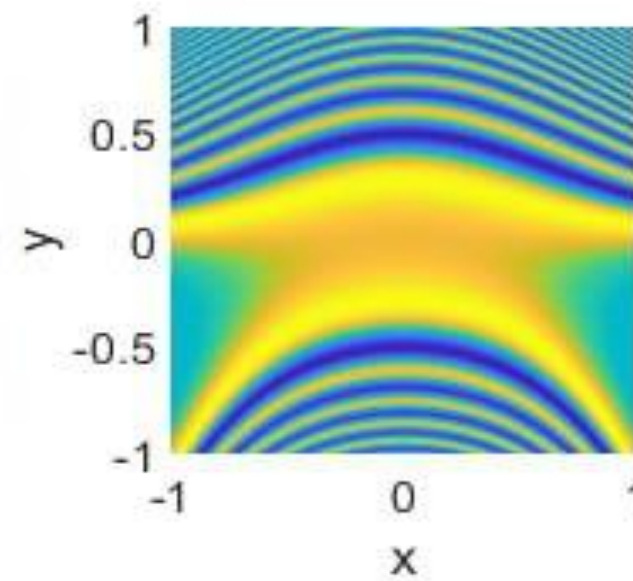
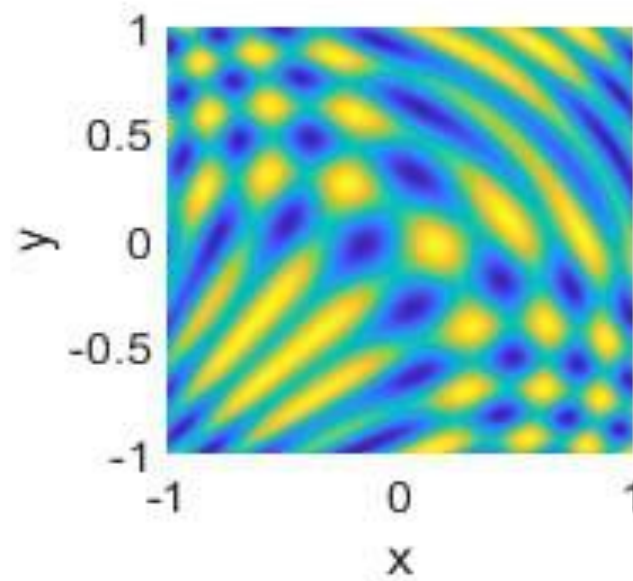
Approx. rank

$k = 5$

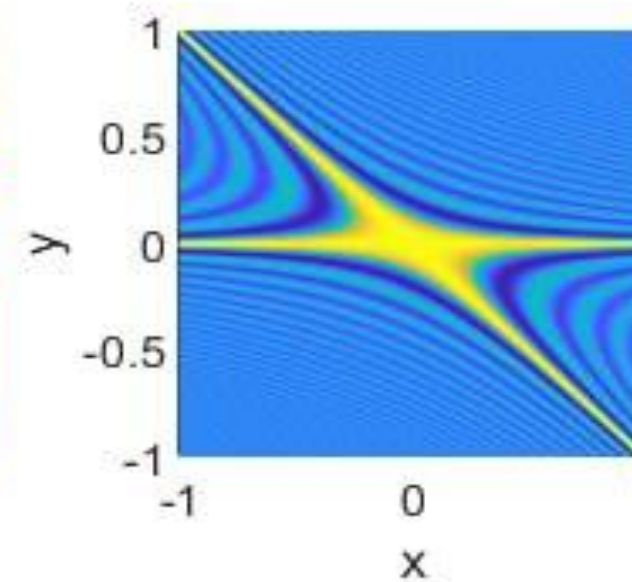
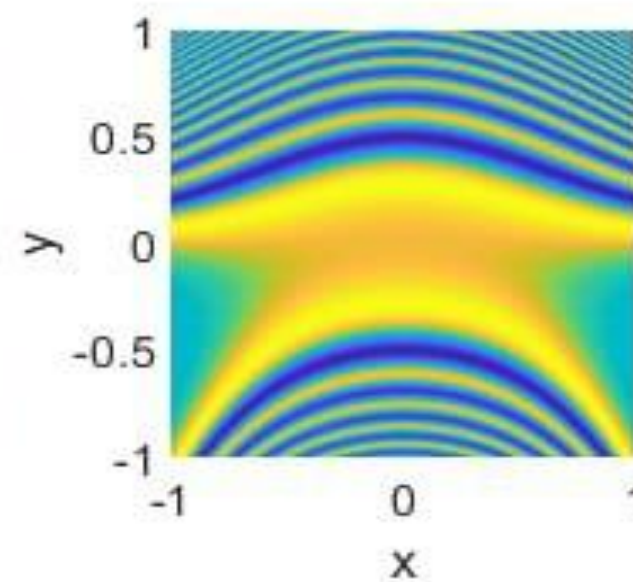
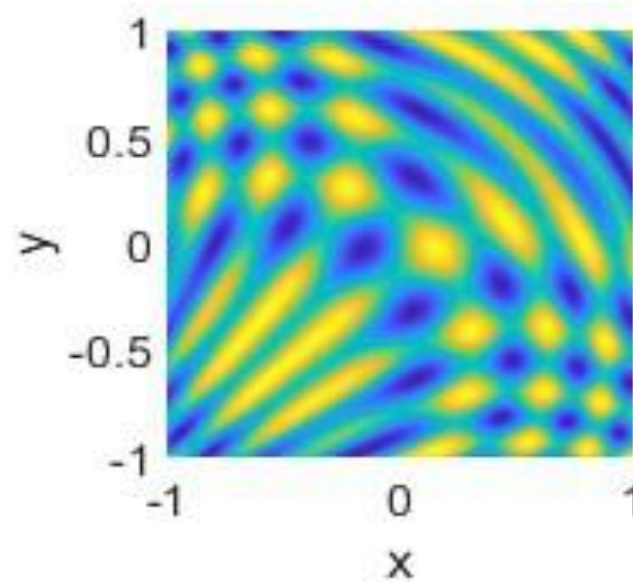
$k = 50$

$k = 100$

Original



Learned

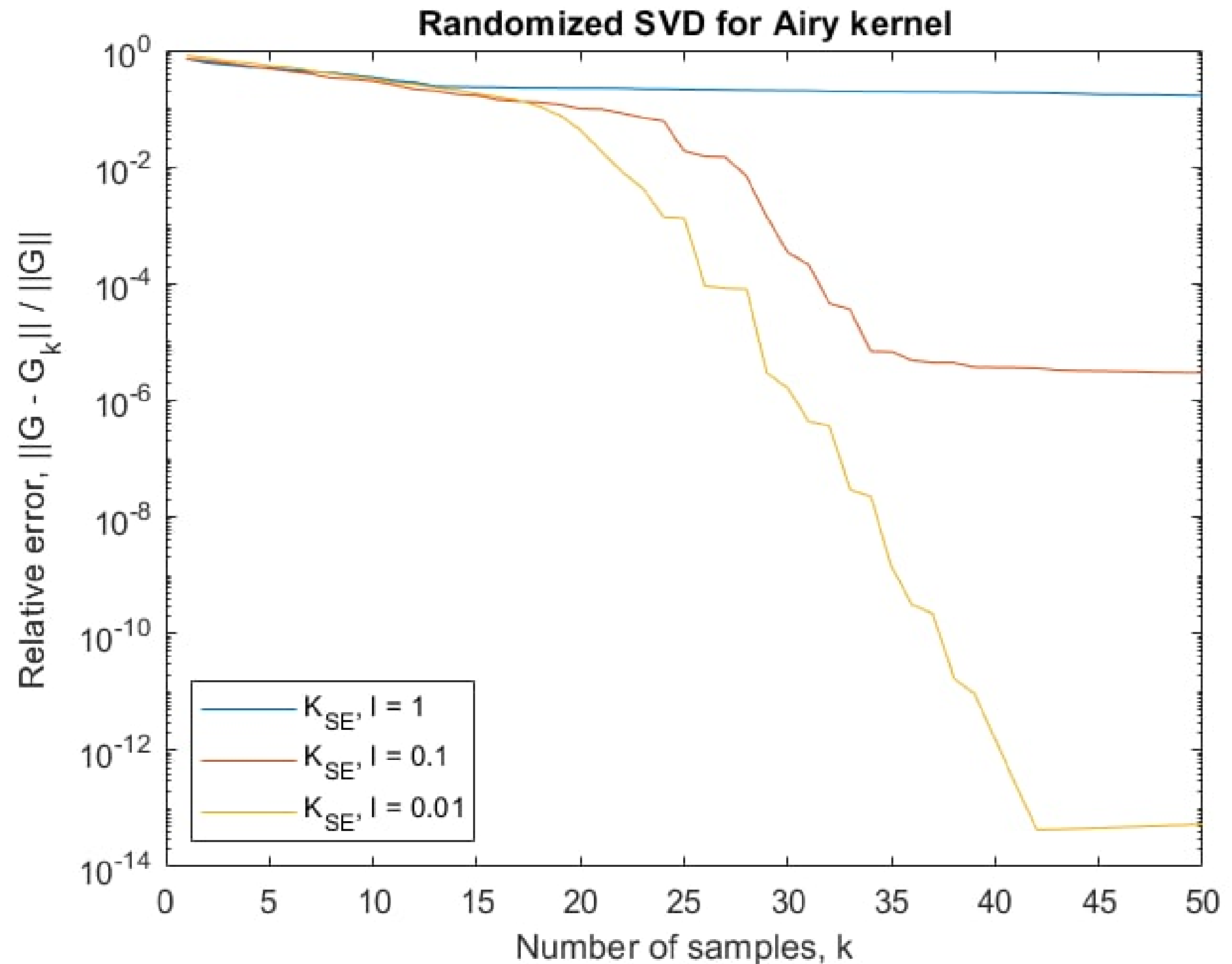


Experiments: accuracy of approximation for Airy kernel

Airy kernel:

$$G(x, y) = \text{Ai}(-13(x^2 y + y^2))$$

$$\text{Ai}(x) = \frac{1}{\pi} \int_0^\infty \cos\left(\frac{t^3}{3} + xt\right) dt, \quad x \in \mathbb{R}$$

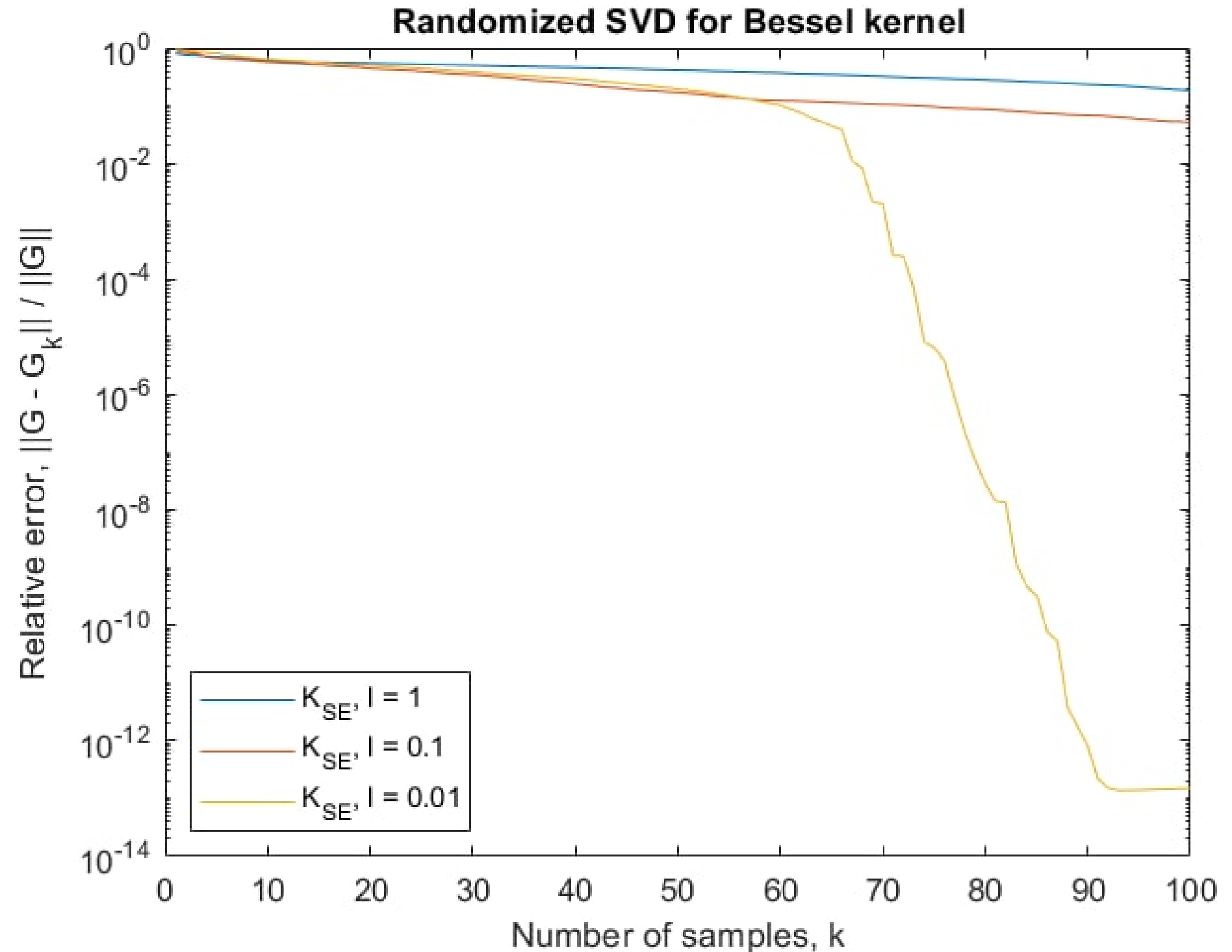


Experiments: accuracy of approximation for Bessel kernel

Bessel kernel:

$$G(x, y) = J_0(100(xy + y^2))$$

$$J_0(x) = \frac{1}{\pi} \int_0^\pi \cos(x \sin t) dt, \quad x \in \mathbb{R}$$



Approximation of matrices using non-standard covariance functions

Theorem 2 *Let \mathbf{A} be an $m \times n$ matrix, $k \geq 1$ an integer, and choose an oversampling parameter $p \geq 4$. If $\mathbf{\Omega} \in \mathbb{R}^{n \times (k+p)}$ is a Gaussian random matrix, where each column is sampled from a*

multivariate Gaussian distribution with covariance matrix $\mathbf{K} \in \mathbb{R}^{n \times n}$, and $\mathbf{QR} = \mathbf{A}\mathbf{\Omega}$ is the economized QR decomposition of $\mathbf{A}\mathbf{\Omega}$, then for all $u, t \geq 1$,

$$\|\mathbf{A} - \mathbf{Q}\mathbf{Q}^* \mathbf{A}\|_F \leq \left(1 + ut \sqrt{(k+p) \frac{3k}{p+1} \frac{\beta_k}{\gamma_k}}\right) \sqrt{\sum_{j=k+1}^n \sigma_j^2(\mathbf{A})}, \quad (2)$$

with failure probability at most $t^{-p} + [ue^{-(u^2-1)/2}]^{k+p}$. Here, $\gamma_k = k/(\lambda_1 \text{Tr}((\mathbf{V}_1^ \mathbf{K} \mathbf{V}_1)^{-1}))$ denotes the covariance quality factor, and $\beta_k = \text{Tr}(\mathbf{\Sigma}_2^2 \mathbf{V}_2^* \mathbf{K} \mathbf{V}_2)/(\lambda_1 \|\mathbf{\Sigma}_2\|_F^2)$, where λ_1 is the largest eigenvalue of \mathbf{K} .*

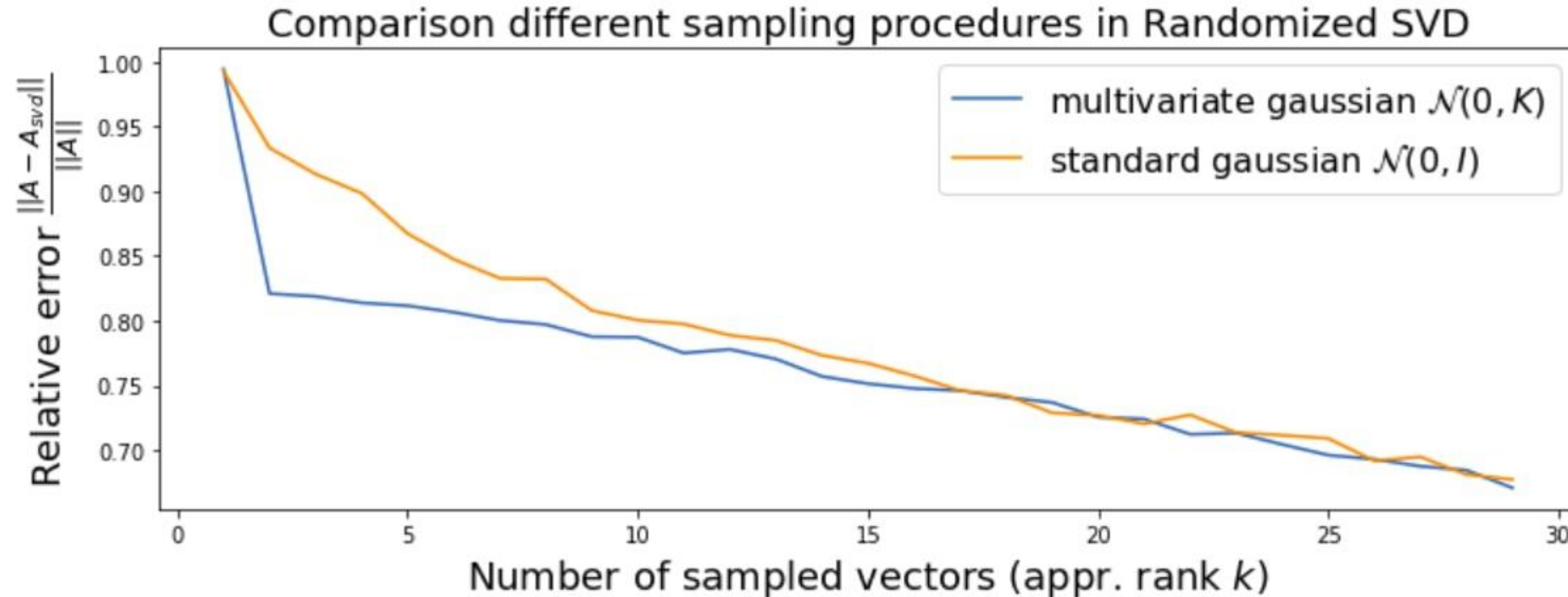
Highlight that, the more prior knowledge of the matrix \mathbf{A} that can be incorporated into the covariance matrix, the better

Approximation of matrices using non-standard covariance functions

Operator: $\mathcal{L}u = d^2u/dx^2 - C \cdot \sin(Kx) \cdot u$, where $x \in [0, 1]$

Estimated matrix: the Green's function of \mathcal{L}

Kernel K is constructed by the Green's function of $\hat{\mathcal{L}}u = -d^2u/dx^2$



Team:

- **Emil Alkin** – performing experiments, presentation;
- **Arkadiy Vladimirov** – the idea, article analysis, algorithm realization;
- **Evgeny Gurov** – article analysis, algorithm realization, organization, github handling;
- **Aleksandr Tolmachev** – finite case algorithm realization.

Thx