

Sparse Spectral Methods for Solving High-Dimensional and Multiscale Elliptic PDEs

Mark Iwen

Michigan State University

Dept. of Mathematics, and

Dept. of Computational Math, Science and Engineering (CMSE)

January 30th, 2026



Joint work with: **Craig Gross** (former Ph. D. student)

Sparse Fourier Transforms for Functions of Many Variables

Theorem (High Dim. SFT [Gross, M.I., Kämmerer, Volkmer, 2022])

Choose any finite $\mathcal{I} \subseteq \mathbb{Z}^d \cap [-K/2, K/2]^d$ you like. There exist Sparse Fourier Transform (SFT) algorithms that use samples from $g : \mathbb{T}^d \rightarrow \mathbb{C}$ (corrupted by errors at most $e_\infty > 0$ in absolute magnitude) to produce a sparse approximation $\hat{g}^s$ to $\hat{g}$ satisfying the error bounds

$$\|\hat{g}^s - \hat{g}\|_2 \lesssim K \left[\frac{\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1}{\sqrt{s}} + \sqrt{s}(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty) \right]$$

$$\|\hat{g}^s - \hat{g}\|_1 \lesssim K [\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1 + s(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty)]$$

- deterministically with complexity $\mathcal{O}(ds^2 \text{polylog}(d, |\mathcal{I}|, K))$,
- and with high probability with complexity $\mathcal{O}(ds \text{polylog}(d, |\mathcal{I}|, K))$.

Sparse Fourier Transforms for Functions of Many Variables

Theorem (High Dim. SFT [Gross, M.I., Kämmerer, Volkmer, 2022])

Choose any finite $\mathcal{I} \subseteq \mathbb{Z}^d \cap [-K/2, K/2]^d$ you like. There exist Sparse Fourier Transform (SFT) algorithms that use samples from $g : \mathbb{T}^d \rightarrow \mathbb{C}$ (corrupted by errors at most $e_\infty > 0$ in absolute magnitude) to produce a sparse approximation $\hat{g}^s$ to $\hat{g}$ satisfying the error bounds

$$\|\hat{g}^s - \hat{g}\|_2 \lesssim K \left[\frac{\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1}{\sqrt{s}} + \sqrt{s}(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty) \right]$$

$$\|\hat{g}^s - \hat{g}\|_1 \lesssim K [\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1 + s(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty)]$$

- deterministically with complexity $\mathcal{O}(ds^2 \text{polylog}(d, |\mathcal{I}|, K))$,
- and with high probability with complexity $\mathcal{O}(ds \text{polylog}(d, |\mathcal{I}|, K))$.

Sparse Fourier Transforms for Functions of Many Variables

Theorem (High Dim. SFT [Gross, M.I., Kämmerer, Volkmer, 2022])

Choose any finite $\mathcal{I} \subseteq \mathbb{Z}^d \cap [-K/2, K/2]^d$ you like. There exist Sparse Fourier Transform (SFT) algorithms that use samples from $g : \mathbb{T}^d \rightarrow \mathbb{C}$ (corrupted by errors at most $e_\infty > 0$ in absolute magnitude) to produce a sparse approximation $\hat{g}^s$ to $\hat{g}$ satisfying the error bounds

$$\|\hat{g}^s - \hat{g}\|_2 \lesssim K \left[\frac{\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1}{\sqrt{s}} + \sqrt{s}(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty) \right]$$

$$\|\hat{g}^s - \hat{g}\|_1 \lesssim K [\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1 + s(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty)]$$

- *deterministically with complexity $\mathcal{O}(ds^2 \text{polylog}(d, |\mathcal{I}|, K))$,*
- *and with high probability with complexity $\mathcal{O}(ds \text{polylog}(d, |\mathcal{I}|, K))$.*

Sparse Fourier Transforms for Functions of Many Variables

Theorem (High Dim. SFT [Gross, M.I., Kämmerer, Volkmer, 2022])

Choose any finite $\mathcal{I} \subseteq \mathbb{Z}^d \cap [-K/2, K/2]^d$ you like. There exist Sparse Fourier Transform (SFT) algorithms that use samples from $g : \mathbb{T}^d \rightarrow \mathbb{C}$ (corrupted by errors at most $e_\infty > 0$ in absolute magnitude) to produce a sparse approximation $\hat{g}^s$ to $\hat{g}$ satisfying the error bounds

$$\|\hat{g}^s - \hat{g}\|_2 \lesssim K \left[\frac{\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1}{\sqrt{s}} + \sqrt{s}(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty) \right]$$

$$\|\hat{g}^s - \hat{g}\|_1 \lesssim K [\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1 + s(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty)]$$

- *deterministically with complexity $\mathcal{O}(ds^2 \text{polylog}(d, |\mathcal{I}|, K))$,*
- *and with high probability with complexity $\mathcal{O}(ds \text{polylog}(d, |\mathcal{I}|, K))$.*

Sparse Fourier Transforms for Functions of Many Variables

Theorem (High Dim. SFT [Gross, M.I., Kämmerer, Volkmer, 2022])

Choose any finite $\mathcal{I} \subseteq \mathbb{Z}^d \cap [-K/2, K/2]^d$ you like. There exist Sparse Fourier Transform (SFT) algorithms that use samples from $g : \mathbb{T}^d \rightarrow \mathbb{C}$ (corrupted by errors at most $e_\infty > 0$ in absolute magnitude) to produce a sparse approximation $\hat{g}^s$ to $\hat{g}$ satisfying the error bounds

$$\|\hat{g}^s - \hat{g}\|_2 \lesssim K \left[\frac{\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1}{\sqrt{s}} + \sqrt{s}(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty) \right]$$

$$\|\hat{g}^s - \hat{g}\|_1 \lesssim K [\|\hat{g}|_{\mathcal{I}} - (\hat{g}|_{\mathcal{I}})_s^{\text{opt}}\|_1 + s(\|\hat{g} - \hat{g}|_{\mathcal{I}}\|_1 + e_\infty)]$$

- *deterministically with complexity $\mathcal{O}(ds^2 \text{polylog}(d, |\mathcal{I}|, K))$,*
- *and with high probability with complexity $\mathcal{O}(ds \text{polylog}(d, |\mathcal{I}|, K))$.*

Model periodic diffusion equation

- Consider the *stationary diffusion equation*

$$\mathcal{L}[a]u := -\nabla \cdot (a \nabla u) = f.$$

- There are three functions (assuming periodicity $\mathbb{T} := \mathbb{R}/\mathbb{Z}$):
 - $a : \mathbb{T}^d \rightarrow \mathbb{R}$ is the diffusion coefficient,
 - $f : \mathbb{T}^d \rightarrow \mathbb{R}$ is the forcing function,
 - and $u : \mathbb{T}^d \rightarrow \mathbb{R}$ is the solution.

Model periodic diffusion equation

- Consider the *stationary diffusion equation*

$$\mathcal{L}[a]u := -\nabla \cdot (a \nabla u) = f.$$

- There are three functions (assuming periodicity $\mathbb{T} := \mathbb{R}/\mathbb{Z}$):
 - $a : \mathbb{T}^d \rightarrow \mathbb{R}$ is the diffusion coefficient,
 - $f : \mathbb{T}^d \rightarrow \mathbb{R}$ is the forcing function,
 - and $u : \mathbb{T}^d \rightarrow \mathbb{R}$ is the solution.

Model periodic diffusion equation

- Consider the *stationary diffusion equation*

$$\mathcal{L}[a]u := -\nabla \cdot (a \nabla u) = f.$$

- There are three functions (assuming periodicity $\mathbb{T} := \mathbb{R}/\mathbb{Z}$):
 - $a : \mathbb{T}^d \rightarrow \mathbb{R}$ is the diffusion coefficient,
 - $f : \mathbb{T}^d \rightarrow \mathbb{R}$ is the forcing function,
 - and $u : \mathbb{T}^d \rightarrow \mathbb{R}$ is the solution.

Model periodic diffusion equation

- Consider the *stationary diffusion equation*

$$\mathcal{L}[a]u := -\nabla \cdot (a \nabla u) = f.$$

- There are three functions (assuming periodicity $\mathbb{T} := \mathbb{R}/\mathbb{Z}$):
 - $a : \mathbb{T}^d \rightarrow \mathbb{R}$ is the diffusion coefficient,
 - $f : \mathbb{T}^d \rightarrow \mathbb{R}$ is the forcing function,
 - and $u : \mathbb{T}^d \rightarrow \mathbb{R}$ is the solution.

Fourier spectral methods in 3 minutes

- Substitute Fourier series for data and solution:

$$-\nabla \cdot (a(x) \nabla u(x)) = f(x)$$

$$-\nabla \cdot \left(\sum_{l \in \mathbb{Z}^d} \hat{a}_l e^{2\pi i l \cdot x} \nabla \sum_{k \in \mathbb{Z}^d} \hat{u}_k e^{2\pi i k \cdot x} \right) = \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x}$$

$$\sum_{l, k \in \mathbb{Z}^d} (2\pi)^2 (l + k) \cdot k \hat{a}_l \hat{u}_k e^{2\pi i (l+k) \cdot x} = \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x}.$$

- Match up Fourier coefficients:

$$\sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

Fourier spectral methods in 3 minutes

- Substitute Fourier series for data and solution:

$$\begin{aligned}
 & -\nabla \cdot (a(x) \nabla u(x)) = f(x) \\
 & -\nabla \cdot \left(\sum_{l \in \mathbb{Z}^d} \hat{a}_l e^{2\pi i l \cdot x} \nabla \sum_{k \in \mathbb{Z}^d} \hat{u}_k e^{2\pi i k \cdot x} \right) = \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x} \\
 & \sum_{l, k \in \mathbb{Z}^d} (2\pi)^2 (l + k) \cdot k \hat{a}_l \hat{u}_k e^{2\pi i (l+k) \cdot x} = \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x}.
 \end{aligned}$$

- Match up Fourier coefficients:

$$\sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

Fourier spectral methods in 3 minutes

- Substitute Fourier series for data and solution:

$$\begin{aligned}
 -\nabla \cdot (a(x) \nabla u(x)) &= f(x) \\
 -\nabla \cdot \left(\sum_{l \in \mathbb{Z}^d} \hat{a}_l e^{2\pi i l \cdot x} \nabla \sum_{k \in \mathbb{Z}^d} \hat{u}_k e^{2\pi i k \cdot x} \right) &= \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x} \\
 \sum_{l, k \in \mathbb{Z}^d} (2\pi)^2 (l + k) \cdot k \hat{a}_l \hat{u}_k e^{2\pi i (l+k) \cdot x} &= \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x}.
 \end{aligned}$$

- Match up Fourier coefficients:

$$\sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

Fourier spectral methods in 3 minutes

- Substitute Fourier series for data and solution:

$$\begin{aligned}
 -\nabla \cdot (a(x) \nabla u(x)) &= f(x) \\
 -\nabla \cdot \left(\sum_{l \in \mathbb{Z}^d} \hat{a}_l e^{2\pi i l \cdot x} \nabla \sum_{k \in \mathbb{Z}^d} \hat{u}_k e^{2\pi i k \cdot x} \right) &= \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x} \\
 \sum_{l, k \in \mathbb{Z}^d} (2\pi)^2 (l + k) \cdot k \hat{a}_l \hat{u}_k e^{2\pi i (l+k) \cdot x} &= \sum_{j \in \mathbb{Z}^d} \hat{f}_j e^{2\pi i j \cdot x}.
 \end{aligned}$$

- Match up Fourier coefficients:

$$\sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? If not, use an SFT!!!

Fourier spectral methods in 3 minutes

- This looks like something we can work with! Just solve for $\hat{u}$:

$$\sum_{k \in \mathbb{Z}^d} L[\hat{a}]_{j,k} \hat{u}_k := \sum_{k \in \mathbb{Z}^d} (2\pi)^2 j \cdot k \hat{a}_{j-k} \hat{u}_k = \hat{f}_j \quad \forall j \in \mathbb{Z}^d.$$

- Except d is huge... (1) need a subset of $\mathbb{Z}^d$... & (2) need $\hat{f}$ and $\hat{a}$
- FFTs save the day?!? They
 - enforce a basis truncation,
 - approximate the data's Fourier coefficients,
 - and are blazing fast ?Kinda? **If not, use an SFT!!!**

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$.

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$.

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$.

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$.

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1.$

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Error analysis

Lemma (Special case of C ea/Strang's lemma [Canuto et al., 2006])

Let $\tilde{\cdot}$ denote an approximate Fourier transform algorithm, and let v have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{I}} \mathcal{L}[\tilde{a}]_{j,k} \hat{v}_k = \tilde{f}_j \quad \forall j \in \mathcal{I}. \quad (1)$$

Then $\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1.$

A Solution?

- 1 Use an SFT to compute $\tilde{a}_k \approx \hat{a}_k$ on $\forall k \in \text{supp}(\hat{a})$.
- 2 Use an SFT to compute $\tilde{f}_k \approx \hat{f}_k$ on $\forall k \in \text{supp}(\hat{f})$.
- 3 Use discovered $\text{supp}(\hat{a})$ and $\text{supp}(\hat{f})$ to construct a "good" set $\mathcal{I} \subset \mathbb{Z}^d$.
- 4 Solve (1) to find the $\hat{v}_k \forall k \in \mathcal{I}$.

Swapping out FFTs for SFTs when $d = 1$

Choose trigonometric polynomials for data

$$a(x) = 2 + \sin(2\pi x),$$

$$f(x) = \cos(2\pi 4x) - 500 \cos(2\pi 75x) + 1000 \cos(2\pi 150x).$$

SFT spectral method

DFT spectral method

- Each frame increases s by 1.
- Takes $s = 3$ to resolve the full solution.
- Only parameter is bandwidth K . Increases by 2 each frame.
- Takes $K \approx 400$ to resolve the full solution.

Swapping out FFTs for SFTs when $d = 2$

Choose trigonometric polynomials for data

$$a(x, y) = 2 + \sin(2\pi(x + 2y)),$$

$$f(x, y) = \cos(2\pi(5x + 3y)) - 500 \cos(2\pi(74x + 76y)) + 1000 \cos(2\pi(151x + 149y)).$$

SFT spectral method

DFT spectral method

The error in the computed solutions is shown as s and K increase each frame of the respective animations. Note that each FFT requires $\mathcal{O}(K^d \log^d(K))$ operations compared to $\mathcal{O}(ds \text{ polylog}(d, |\mathcal{I}|, K))$ for an SFT.

But How Should we Choose $\mathcal{I}$?

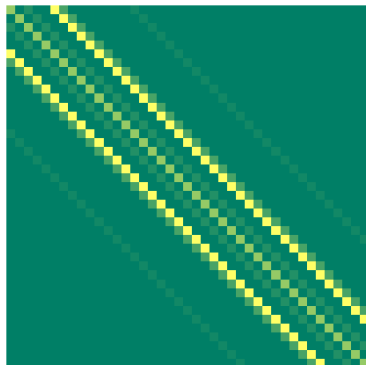
SFTs Control Last Two Terms in C  a's Lemma... & for the First...???

$$\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$$

- Assume data is Fourier sparse.
- Let's take a closer look at our Galerkin operator

$$L[\hat{a}] = ((2\pi)^2 j \cdot k \hat{a}_{j-k})_{j,k \in \mathbb{Z}^d}.$$

- Only elements of $\hat{u}$ spaced out according to $\text{supp}(\hat{a})$ will interact in $L[\hat{a}]\hat{u}$.



But How Should we Choose $\mathcal{I}$?

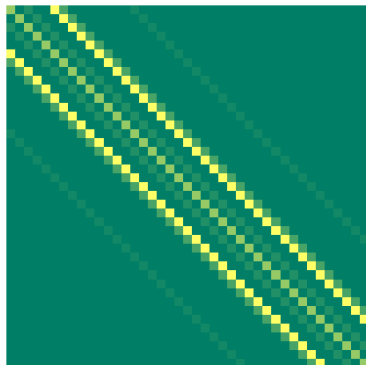
SFTs Control Last Two Terms in C  a's Lemma... & for the First...???

$$\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$$

- Assume data is Fourier sparse.
- Let's take a closer look at our Galerkin operator

$$L[\hat{a}] = ((2\pi)^2 j \cdot k \hat{a}_{j-k})_{j,k \in \mathbb{Z}^d}.$$

- Only elements of $\hat{u}$ spaced out according to $\text{supp}(\hat{a})$ will interact in $L[\hat{a}]\hat{u}$.



But How Should we Choose $\mathcal{I}$?

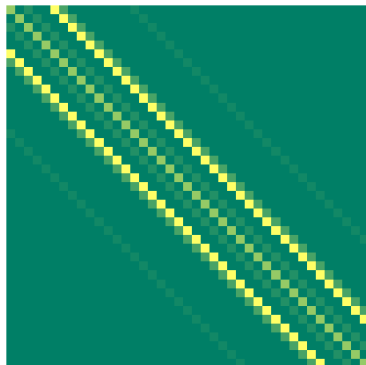
SFTs Control Last Two Terms in C  a's Lemma... & for the First...???

$$\|u - v\|_{H^1} \lesssim_{a,f} \|u - u|_{\mathcal{I}}\|_{H^1} + \|\hat{f} - \tilde{f}\|_2 + \|\hat{a} - \tilde{a}\|_1$$

- Assume data is Fourier sparse.
- Let's take a closer look at our Galerkin operator

$$L[\hat{a}] = ((2\pi)^2 j \cdot k \hat{a}_{j-k})_{j,k \in \mathbb{Z}^d}.$$

- Only elements of $\hat{u}$ spaced out according to $\text{supp}(\hat{a})$ will interact in $L[\hat{a}]\hat{u}$.



“Stamp” sets

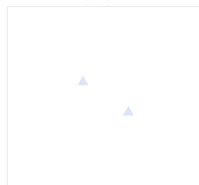
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\text{supp}(\hat{f}) = \mathcal{S}^0$



“Stamp” sets

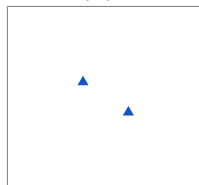
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\text{supp}(\hat{f}) = \mathcal{S}^0$

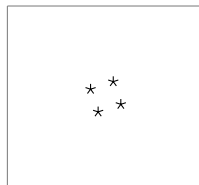


“Stamp” sets

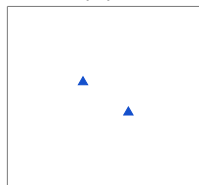
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\text{supp}(\hat{f}) = \mathcal{S}^0$

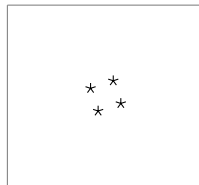


“Stamp” sets

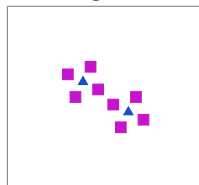
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\mathcal{S}^1$

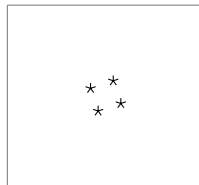


“Stamp” sets

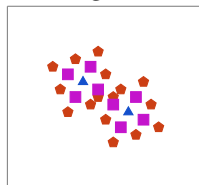
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\mathcal{S}^2$

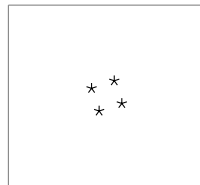


“Stamp” sets

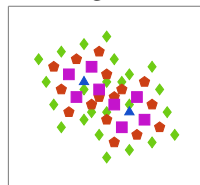
- Consider $\text{supp}(\hat{a})$.
- Now $\text{supp}(\hat{f})$.
- Let

$$\mathcal{S}^N := \begin{cases} \text{supp}(\hat{f}) & N = 0 \\ \mathcal{S}^{N-1} + \text{supp}(\hat{a}) & N > 0. \end{cases}$$

$\text{supp}(\hat{a})$



$\mathcal{S}^3$



Error analysis of spectral method

Theorem (Sparse spectral algorithm [Gross, M.I., 2023])

Let a^s, f^s be from high-dimensional SFT previously discussed, and let $u^{s,N}$ have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{S}^N} L[\hat{a}^s]_{j,k} \hat{u}_k^{s,N} = \hat{f}_j^s \quad \forall j \in \mathcal{S}^N.$$

Then for a decay rate $A < 1$ characterized by the ellipticity of a ,

$$\|u - u^{s,N}\|_{H^1} \lesssim_{a,f} A^{N+1} + \|\hat{f} - \hat{f}^s\|_2 + \|\hat{a} - \hat{a}^s\|_1.$$

With a randomly chosen rank-1 lattice w.h.p. we have

$$\left\| \hat{f} - \hat{f}^s \right\|_2 \lesssim K\sqrt{s} \left\| \hat{f} - \left(\hat{f}|_{[-K/2, K/2]^d} \right)_s^{\text{opt}} \right\|_1$$

Uses theoretical SFT error bounds [Gross, M.I., Kämmerer, Volkmer, 2022]

Error analysis of spectral method

Theorem (Sparse spectral algorithm [Gross, M.I., 2023])

Let a^s, f^s be from high-dimensional SFT previously discussed, and let $u^{s,N}$ have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{S}^N} L[\hat{a}^s]_{j,k} \hat{u}_k^{s,N} = \hat{f}_j^s \quad \forall j \in \mathcal{S}^N.$$

Then for a decay rate $A < 1$ characterized by the ellipticity of a ,

$$\|u - u^{s,N}\|_{H^1} \lesssim_{a,f} A^{N+1} + \|\hat{f} - \hat{f}^s\|_2 + \|\hat{a} - \hat{a}^s\|_1.$$

With a randomly chosen rank-1 lattice w.h.p. we have

$$\|\hat{f} - \hat{f}^s\|_2 \lesssim K\sqrt{s} \left\| \hat{f} - \left(\hat{f}|_{[-K/2, K/2]^d} \right)_s^{\text{opt}} \right\|_1$$

Uses theoretical SFT error bounds [Gross, M.I., Kämmerer, Volkmer, 2022]

Error analysis of spectral method

Theorem (Sparse spectral algorithm [Gross, M.I., 2023])

Let a^s, f^s be from high-dimensional SFT previously discussed, and let $u^{s,N}$ have Fourier coefficients solving the matrix equation

$$\sum_{k \in \mathcal{S}^N} L[\hat{a}^s]_{j,k} \hat{u}_k^{s,N} = \hat{f}_j^s \quad \forall j \in \mathcal{S}^N.$$

Then for a decay rate $A < 1$ characterized by the ellipticity of a ,

$$\|u - u^{s,N}\|_{H^1} \lesssim_{a,f} A^{N+1} + \|\hat{f} - \hat{f}^s\|_2 + \|\hat{a} - \hat{a}^s\|_1.$$

With a randomly chosen rank-1 lattice w.h.p. we have

$$\|\hat{f} - \hat{f}^s\|_2 \lesssim K\sqrt{s} \left\| \hat{f} - \left(\hat{f}|_{[-K/2, K/2]^d} \right)_s^{\text{opt}} \right\|_1$$

Uses theoretical SFT error bounds [Gross, M.I., Kämmerer, Volkmer, 2022]

More on stamping factor



Two quantities of diffusion coefficient, a , determine exponential decay:

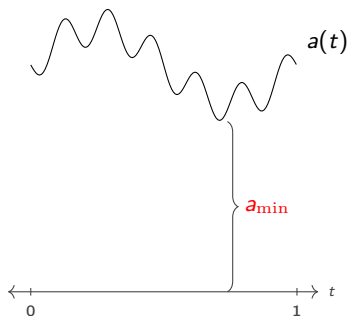
- Minimum: $a_{\min}$.
- Deviation from mean:
 $\|a - \hat{a}_0\|_{L^\infty}$.

The decay factor has the form

$$A := \frac{\|a - \hat{a}_0\|_{L^\infty}}{a_{\min} - 2\|a - \hat{a}_0\|_{L^\infty}}.$$



More on stamping factor



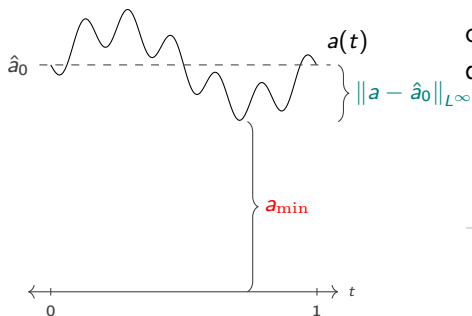
Two quantities of diffusion coefficient, a , determine exponential decay:

- Minimum: $a_{\min}$.
- Deviation from mean:
 $\|a - \hat{a}_0\|_{L^\infty}$.

The decay factor has the form

$$A := \frac{\|a - \hat{a}_0\|_{L^\infty}}{a_{\min} - 2\|a - \hat{a}_0\|_{L^\infty}}.$$

More on stamping factor



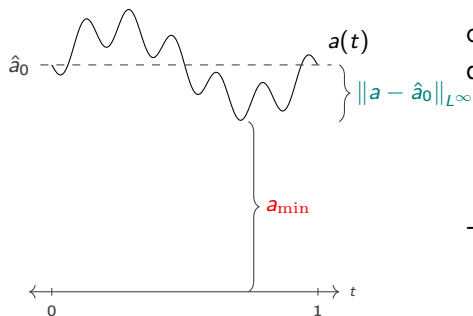
Two quantities of diffusion coefficient, a , determine exponential decay:

- Minimum: $a_{\min}$.
- Deviation from mean:
 $\|a - \hat{a}_0\|_{L^\infty}$.

The decay factor has the form

$$A := \frac{\|a - \hat{a}_0\|_{L^\infty}}{a_{\min} - 2\|a - \hat{a}_0\|_{L^\infty}}.$$

More on stamping factor



Two quantities of diffusion coefficient, a , determine exponential decay:

- Minimum: $a_{\min}$.
- Deviation from mean:
 $\|a - \hat{a}_0\|_{L^\infty}$.

The decay factor has the form

$$A := \frac{\|a - \hat{a}_0\|_{L^\infty}}{a_{\min} - 2\|a - \hat{a}_0\|_{L^\infty}}.$$

Complexity analysis of spectral method

- The algorithm uses two SFTs and a $|\mathcal{S}^N| \times |\mathcal{S}^N|$ (sparse) matrix system solve.
- Each SFT succeeds with high probability with complexity $\mathcal{O}(ds \text{ polylog}(d, s, K))$.
- $|\mathcal{S}^N|$ can be upper bounded by

$$|\mathcal{S}^N| = \mathcal{O} \left(\max(s, 2N + 1)^{\min(s, 2N+1)} \right).$$

- So dependence on ambient dimension is linear.
- And exponential dependence on N is computationally mitigated.

Complexity analysis of spectral method

- The algorithm uses two SFTs and a $|\mathcal{S}^N| \times |\mathcal{S}^N|$ (sparse) matrix system solve.
- Each SFT succeeds with high probability with complexity $\mathcal{O}(ds \text{ polylog}(d, s, K))$.
- $|\mathcal{S}^N|$ can be upper bounded by

$$|\mathcal{S}^N| = \mathcal{O} \left(\max(s, 2N + 1)^{\min(s, 2N + 1)} \right).$$

- So dependence on ambient dimension is linear.
- And exponential dependence on N is computationally mitigated.

Complexity analysis of spectral method

- The algorithm uses two SFTs and a $|\mathcal{S}^N| \times |\mathcal{S}^N|$ (sparse) matrix system solve.
- Each SFT succeeds with high probability with complexity $\mathcal{O}(ds \text{ polylog}(d, s, K))$.
- $|\mathcal{S}^N|$ can be upper bounded by

$$|\mathcal{S}^N| = \mathcal{O} \left(\max(s, 2N + 1)^{\min(s, 2N+1)} \right).$$

- So dependence on ambient dimension is linear.
- And exponential dependence on N is computationally mitigated.

Complexity analysis of spectral method

- The algorithm uses two SFTs and a $|\mathcal{S}^N| \times |\mathcal{S}^N|$ (sparse) matrix system solve.
- Each SFT succeeds with high probability with complexity $\mathcal{O}(ds \text{ polylog}(d, s, K))$.
- $|\mathcal{S}^N|$ can be upper bounded by

$$|\mathcal{S}^N| = \mathcal{O} \left(\max(s, 2N + 1)^{\min(s, 2N+1)} \right).$$

- So dependence on ambient dimension is linear.
- And exponential dependence on N is computationally mitigated.

Complexity analysis of spectral method

- The algorithm uses two SFTs and a $|\mathcal{S}^N| \times |\mathcal{S}^N|$ (sparse) matrix system solve.
- Each SFT succeeds with high probability with complexity $\mathcal{O}(ds \text{ polylog}(d, s, K))$.
- $|\mathcal{S}^N|$ can be upper bounded by

$$|\mathcal{S}^N| = \mathcal{O} \left(\max(s, 2N + 1)^{\min(s, 2N+1)} \right).$$

- So dependence on ambient dimension is linear.
- And exponential dependence on N is computationally mitigated.

High-dimensional example

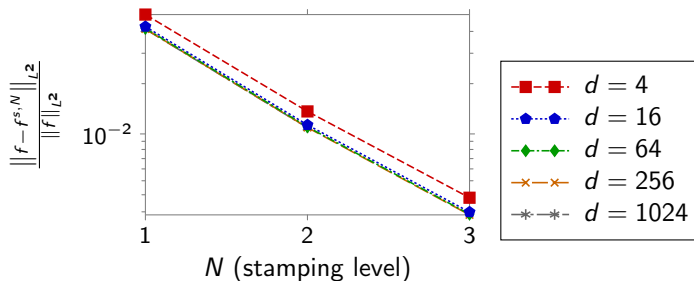


Figure: Proxy error solving $\nabla \cdot (a \nabla u) = f$

- a sparsity is 51.
- f sparsity is 2.
- Frequencies are chosen randomly in bandwidth of 1000 in each dimension.

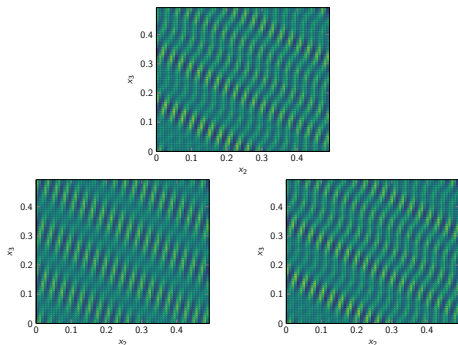
3D advection-diffusion-reaction example

$$-\nabla \cdot (a(x)\nabla u(x)) + b(x) \cdot \nabla u(x) + c(x)u(x) = f(x).$$

Each term is ≈ 20 sparse for 90 total operator terms and 10 forcing terms.

s	N	$\ f - f^{s,N}\ _{L^2} / \ f\ _{L^2}$
8	1	0.518
	2	0.518
20	1	0.054
	2	0.031

Table: Error in approximating ADR solution.



References



C. Gross, M.I., L. Kämmerer, and T. Volkmer,
“Sparse fourier transforms on rank-1 lattices for the rapid and
low-memory approximation of functions of many variables,”
Sampling Theory, Signal Processing, and Data Analysis, 20:1, 2022.



Claudio Canuto, M. Yousuff Hussaini, Alfio Quarteroni, and Thomas A.
Zang.
Spectral Methods: Fundamentals in Single Domains.
Scientific Computation. Springer-Verlag, Berlin Heidelberg, 2006.



C. Gross, M.I.,
“Sparse spectral methods for solving high-dimensional and multiscale
elliptic PDEs,”
Foundations of Computational Mathematics, to appear.