

torch-sla: Differentiable Sparse Linear Algebra with Adjoint Solvers and Sparse Tensor Parallelism for PyTorch

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<https://github.com/walkerchi/torch-sla>

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Abstract

We present `torch-sla`, an open-source PyTorch library for differentiable sparse linear algebra. The library addresses two fundamental challenges: (1) **Adjoint-based differentiation** for linear and nonlinear sparse solvers, achieving $\mathcal{O}(\text{nnz})$ memory complexity for computational graphs regardless of solver iterations; and (2) **Sparse Tensor Parallel** computing via domain decomposition with halo exchange, enabling distributed sparse operations across multiple GPUs. `torch-sla` supports multiple backends (SciPy, cuDSS, PyTorch-native) and scales to **169 million DOF on a single GPU** and **400 million DOF on 3 GPUs** with near-linear scaling. Benchmarks demonstrate correct gradient computation verified against finite differences. Code is available at <https://github.com/walkerchi/torch-sla>.

1 Introduction

Sparse linear systems $\mathbf{Ax} = \mathbf{b}$ are fundamental to scientific computing. They arise in finite element analysis [Hughes, 2012], graph neural networks [Kipf and Welling, 2017, Veličković et al., 2018], physics-informed machine learning [Raissi et al., 2019, Lu et al., 2021], and computational fluid dynamics [Jasak et al., 2007, Kochkov et al., 2021]. With the rise of differentiable programming and neural operators [Li et al., 2020, Brandstetter et al., 2022], there is growing demand for sparse solvers that integrate with automatic differentiation frameworks like PyTorch [Paszke et al., 2019].

The challenge of differentiating through solvers. Consider a loss function $\mathcal{L}(\mathbf{x})$ where $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$ is obtained by solving a linear system. To train neural networks that interact with such solvers, we need gradients $\partial\mathcal{L}/\partial\mathbf{A}$ and $\partial\mathcal{L}/\partial\mathbf{b}$. A naive approach—differentiating through each iteration of an iterative solver—creates $\mathcal{O}(k)$ nodes in the computational graph, where k may be thousands of iterations. This leads to memory explosion and slow backward passes.

The challenge of scale. Industrial problems often exceed single-GPU memory. A 3D finite element mesh with 10 million nodes produces a sparse matrix requiring tens of gigabytes. Distributed computing is essential, but sparse matrix operations require careful communication patterns (halo exchange) that are non-trivial to implement correctly with gradient support. Our library demonstrates scaling to **400 million DOF on 3 GPUs**, enabling industrial-scale differentiable simulations.

This paper introduces `torch-sla`^{*}, addressing both challenges with two key innovations:

- **Adjoint-based differentiation** (§3.2): We implement the adjoint method for linear solves, eigenvalue problems, and nonlinear systems. This achieves $\mathcal{O}(1)$ computational graph nodes and $\mathcal{O}(\text{nnz})$ memory, independent of solver iterations.

^{*}Code available at <https://github.com/walkerchi/torch-sla>. Install via `pip install torch-sla`.

- **Sparse tensor parallelism** (§3.3): We implement domain decomposition with automatic halo exchange following industrial CFD/FEM practices. This enables multi-GPU computing with gradient support.

2 Related Work

Differentiable linear algebra. JAX [Bradbury et al., 2018] provides differentiable sparse CG, but naive differentiation through iterations creates $\mathcal{O}(k)$ graph nodes. Blondel et al. [2022] formalize implicit differentiation for optimization layers. OptNet [Amos and Kolter, 2017] and cvxpylayers [Agrawal et al., 2019] handle convex optimization. Deep equilibrium models [Bai et al., 2019] and Jacobian-free backpropagation [Fung et al., 2022] address implicit layers but focus on fixed-point iterations rather than sparse linear systems.

Sparse solvers and GPU acceleration. SciPy [Virtanen et al., 2020] provides SuperLU/UMFPACK for CPU. For GPU, NVIDIA cuDSS [NVIDIA Corporation, 2024] offers direct solvers, while AmgX [Naumov et al., 2015] provides algebraic multigrid with excellent scalability. Recent surveys [Li et al., 2024] cover sparse matrix computations on modern GPUs. None of these natively support PyTorch autograd.

Distributed sparse computing. PETSc [Balay et al., 2023], Trilinos [Heroux et al., 2005], and hypre [Falgout and Yang, 2002] implement distributed sparse linear algebra with sophisticated preconditioners. OpenFOAM [Jasak et al., 2007] uses domain decomposition for CFD. We bring these industrial patterns to PyTorch with automatic differentiation.

Learned solvers and preconditioners. Recent work explores learning components of iterative solvers: learned multigrid prolongation [Greenfeld et al., 2019], GNN-based AMG [Luz et al., 2020], and learned interface conditions for domain decomposition [Taghibakhshi et al., 2024]. These complement our library by providing learnable components that can be trained end-to-end.

3 Methodology

We first introduce the background on sparse linear systems (§3.1), then present our adjoint-based differentiation approach (§3.2), and finally describe our distributed computing implementation (§3.3).

3.1 Preliminaries: Sparse Linear Systems

A sparse linear system $\mathbf{Ax} = \mathbf{b}$ has a matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ with $\text{nnz} \ll n^2$ non-zero entries. We store matrices in coordinate (COO) format: three arrays for row indices, column indices, and values.

Direct solvers (LU, Cholesky factorization) compute exact solutions but require $\mathcal{O}(n^{1.5})$ memory for 2D problems due to fill-in—new non-zeros created during factorization [George, 1973]. For a 2D Poisson problem with n unknowns, the factored matrix has $\mathcal{O}(n \log n)$ non-zeros instead of the original $\mathcal{O}(n)$.

Iterative solvers (Conjugate Gradient, BiCGStab, GMRES) maintain $\mathcal{O}(\text{nnz})$ memory by never forming the factorization. However, they require $\mathcal{O}(\sqrt{\kappa})$ iterations for CG where κ is the condition number [Saad, 2003]. Each iteration performs one sparse matrix-vector multiplication (SpMV) costing $\mathcal{O}(\text{nnz})$.

The differentiation problem. Given loss $\mathcal{L}(\mathbf{x})$ where $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$, we need gradients with respect to both \mathbf{b} and the non-zero values of \mathbf{A} . If we differentiate through k iterations of CG, the computational graph has $\mathcal{O}(k)$ nodes, each storing intermediate vectors. For $k = 1000$ iterations and $n = 10^6$, this requires ~ 80 GB just for the graph. Our adjoint approach reduces this to $\mathcal{O}(1)$ nodes.

3.2 Adjoint-Based Differentiation

The adjoint method computes gradients through implicit functions without storing intermediate solver states. We present it for linear systems, eigenvalue problems, and nonlinear systems.

3.2.1 Linear Systems

Consider $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$. Rather than differentiating through the solver iterations, we use the *implicit function theorem*. The solution satisfies $\mathbf{Ax} - \mathbf{b} = \mathbf{0}$. Differentiating implicitly:

$$d\mathbf{A} \cdot \mathbf{x} + \mathbf{A} \cdot d\mathbf{x} = d\mathbf{b} \implies d\mathbf{x} = \mathbf{A}^{-1}(d\mathbf{b} - d\mathbf{A} \cdot \mathbf{x}) \quad (1)$$

Table 1: Complexity comparison: naive vs. adjoint differentiation through iterative solver with k iterations, n unknowns, and nnz non-zeros.

	Naive (through iterations)	Adjoint (ours)
Computational graph nodes	$\mathcal{O}(k)$	$\mathcal{O}(1)$
Memory for graph	$\mathcal{O}(k \cdot n)$	$\mathcal{O}(n + \text{nnz})$
Backward pass time	$\mathcal{O}(k \cdot \text{nnz})$	$\mathcal{O}(T_{\text{solve}} + \text{nnz})$

For a scalar loss $\mathcal{L}(\mathbf{x})$, the chain rule gives:

$$d\mathcal{L} = \left(\frac{\partial \mathcal{L}}{\partial \mathbf{x}} \right)^\top d\mathbf{x} = \left(\frac{\partial \mathcal{L}}{\partial \mathbf{x}} \right)^\top \mathbf{A}^{-1} (d\mathbf{b} - d\mathbf{A} \cdot \mathbf{x}) \quad (2)$$

Define the **adjoint variable** $\boldsymbol{\lambda} = \mathbf{A}^{-\top} \frac{\partial \mathcal{L}}{\partial \mathbf{x}}$, solved via $\mathbf{A}^\top \boldsymbol{\lambda} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}}$. Then the gradients are:

$$\boxed{\frac{\partial \mathcal{L}}{\partial \mathbf{b}} = \boldsymbol{\lambda}, \quad \frac{\partial \mathcal{L}}{\partial \mathbf{A}_{ij}} = -\boldsymbol{\lambda}_i \cdot \mathbf{x}_j} \quad (3)$$

Complexity analysis. Table 1 compares naive differentiation (through iterations) with our adjoint approach.

The forward solve computes \mathbf{x} in time T_{solve} . The backward pass:

1. Solves $\mathbf{A}^\top \boldsymbol{\lambda} = \frac{\partial \mathcal{L}}{\partial \mathbf{x}}$: $\mathcal{O}(T_{\text{solve}})$ time
2. Computes $\frac{\partial \mathcal{L}}{\partial \mathbf{A}_{ij}} = -\boldsymbol{\lambda}_i \mathbf{x}_j$ for each non-zero: $\mathcal{O}(\text{nnz})$ time

Algorithm. The complete procedure is shown below:

Algorithm 1: Adjoint Linear Solve

Input: Sparse matrix \mathbf{A} (values, rows, cols), RHS \mathbf{b}

Output: Solution \mathbf{x} , gradients in backward pass

Forward pass:

1. $\mathbf{x} \leftarrow \text{solve}(\mathbf{A}, \mathbf{b})$ *// Any solver: CG, LU, etc.*
2. Store (\mathbf{A}, \mathbf{x}) for backward

Backward pass: (given $\partial \mathcal{L}/\partial \mathbf{x}$)

1. $\boldsymbol{\lambda} \leftarrow \text{solve}(\mathbf{A}^\top, \partial \mathcal{L}/\partial \mathbf{x})$ *// One adjoint solve*
2. $\partial \mathcal{L}/\partial \mathbf{b} \leftarrow \boldsymbol{\lambda}$
3. For each non-zero (i, j) : $\partial \mathcal{L}/\partial \mathbf{A}_{ij} \leftarrow -\boldsymbol{\lambda}_i \cdot \mathbf{x}_j$ *// $\mathcal{O}(\text{nnz})$ total*

3.2.2 Eigenvalue Problems

For symmetric eigenvalue problem $\mathbf{A}\mathbf{v} = \lambda\mathbf{v}$ with normalized eigenvector $\|\mathbf{v}\| = 1$, the gradient of eigenvalue λ with respect to matrix entries is remarkably simple [Magnus, 1985]:

$$\frac{\partial \lambda}{\partial \mathbf{A}_{ij}} = v_i \cdot v_j \quad (4)$$

This is the outer product $\mathbf{v}\mathbf{v}^\top$ restricted to the sparsity pattern. For k eigenvalues, the total cost is $\mathcal{O}(k \cdot \text{nnz})$.

3.2.3 Nonlinear Systems

For nonlinear system $\mathbf{F}(\mathbf{u}, \boldsymbol{\theta}) = \mathbf{0}$ with solution $\mathbf{u}^*(\boldsymbol{\theta})$ and loss $\mathcal{L}(\mathbf{u}^*)$, implicit differentiation gives:

$$\mathbf{J}^\top \boldsymbol{\lambda} = \frac{\partial \mathcal{L}}{\partial \mathbf{u}}, \quad \frac{\partial \mathcal{L}}{\partial \boldsymbol{\theta}} = -\boldsymbol{\lambda}^\top \frac{\partial \mathbf{F}}{\partial \boldsymbol{\theta}} \quad (5)$$

where $\mathbf{J} = \frac{\partial \mathbf{F}}{\partial \mathbf{u}}$ is the Jacobian at the solution.

Algorithm 2: Newton-Raphson with Adjoint Gradients

Input: Residual function $\mathbf{F}(\mathbf{u}, \boldsymbol{\theta})$, initial guess \mathbf{u}_0

Output: Solution \mathbf{u}^*

Forward (Newton iteration):

1. $\mathbf{u} \leftarrow \mathbf{u}_0$
2. **while** $\|\mathbf{F}(\mathbf{u}, \boldsymbol{\theta})\| > \epsilon$ **do:**
 - (a) $\mathbf{J} \leftarrow \partial \mathbf{F} / \partial \mathbf{u}$ *// Jacobian via autograd*
 - (b) $\Delta \mathbf{u} \leftarrow \text{solve}(\mathbf{J}, -\mathbf{F})$
 - (c) $\mathbf{u} \leftarrow \mathbf{u} + \alpha \Delta \mathbf{u}$ *// α from line search*
3. Store $(\mathbf{u}^*, \mathbf{J}, \boldsymbol{\theta})$

Backward: (given $\partial \mathcal{L} / \partial \mathbf{u}^*$)

1. $\boldsymbol{\lambda} \leftarrow \text{solve}(\mathbf{J}^\top, \partial \mathcal{L} / \partial \mathbf{u}^*)$ *// One adjoint solve*
2. $\partial \mathcal{L} / \partial \boldsymbol{\theta} \leftarrow -\boldsymbol{\lambda}^\top \partial \mathbf{F} / \partial \boldsymbol{\theta}$ *// VJP via autograd*

Memory analysis. Forward: $\mathcal{O}(n + \text{nnz})$ for solution and Jacobian. Backward: $\mathcal{O}(n)$ for adjoint variable. Total: $\mathcal{O}(n + \text{nnz})$, independent of Newton iterations.

3.3 Sparse Tensor Parallel Computing

For problems exceeding single-GPU memory, we implement domain decomposition with halo exchange—the standard approach in industrial CFD/FEM codes like OpenFOAM and Ansys Fluent.

3.3.1 Domain Decomposition

Given a sparse matrix \mathbf{A} corresponding to a mesh or graph, we partition the n nodes into P subdomains. Each process p owns nodes \mathcal{O}_p (owned nodes) and maintains copies of neighboring nodes \mathcal{H}_p (halo/ghost nodes) needed for local computation.

Partitioning strategies:

- **METIS** [Karypis and Kumar, 1998]: Graph partitioning minimizing edge cuts for load balancing
- **RCB**: Recursive Coordinate Bisection using node coordinates
- **Contiguous**: Simple row-based partitioning (fallback)

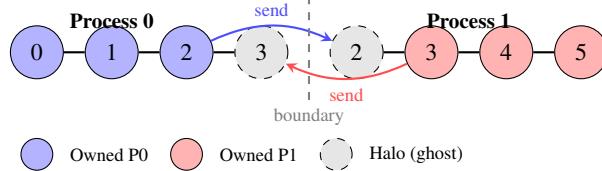


Figure 1: Halo exchange in domain decomposition. Each process owns a subset of nodes (solid colored) and maintains halo copies of boundary neighbors (dashed). Before SpMV, processes exchange updated values at partition boundaries via peer-to-peer communication.

3.3.2 Halo Exchange

The key operation in distributed sparse computing is **halo exchange**: before each SpMV, processes must exchange boundary values with neighbors. Figure 1 illustrates this concept.

Algorithm 3: Distributed SpMV with Halo Exchange

Input: Local vector $\mathbf{x}_{\text{local}}$, neighbor map, local matrix $\mathbf{A}_{\text{local}}$

Output: Result $\mathbf{y}_{\text{owned}}$

Phase 1: Initiate async communication

1. **for** each neighbor q **do**:
 - (a) `async_send(my boundary values to q)`
 - (b) `async_recv(halo values from q)`

Phase 2: Wait for completion

1. `synchronize_all()`

Phase 3: Local computation

1. $\mathbf{y}_{\text{owned}} \leftarrow \mathbf{A}_{\text{local}} \cdot \mathbf{x}_{\text{local}}$ *// Uses owned + halo*

3.3.3 Distributed Conjugate Gradient

Building on distributed SpMV, we implement distributed CG. Each iteration requires:

- One halo exchange (in SpMV)
- Two `all_reduce` operations for global dot products

Algorithm 4: Distributed Conjugate Gradient

Input: Distributed \mathbf{A} , local RHS $\mathbf{b}_{\text{owned}}$, tolerance ϵ

Output: Solution $\mathbf{x}_{\text{owned}}$

1. $\mathbf{x} \leftarrow \mathbf{0}, \mathbf{r} \leftarrow \mathbf{b}_{\text{owned}}, \mathbf{p} \leftarrow \mathbf{r}$
2. $\rho \leftarrow \text{all_reduce}(\mathbf{r}^\top \mathbf{r}, \text{SUM})$ *// Global dot product*

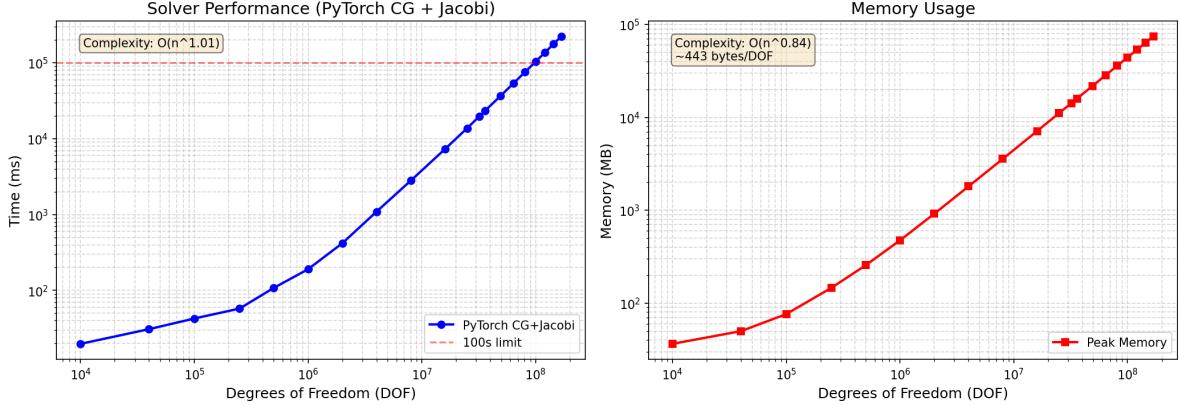


Figure 2: Single-GPU benchmark results showing performance, memory usage, and residual across solver backends (SciPy, cuDSS, PyTorch CG) on 2D Poisson equation with H200 GPU.

Table 2: Single-GPU benchmark on 2D Poisson (5-point stencil), H200, float64.

DOF	SciPy	cuDSS	PyTorch CG	Memory	Residual
10K	24 ms	128 ms	20 ms	36 MB	10^{-9}
100K	29 ms	630 ms	43 ms	76 MB	10^{-7}
1M	19.4 s	7.3 s	190 ms	474 MB	10^{-7}
2M	52.9 s	15.6 s	418 ms	916 MB	10^{-7}
16M	OOM	OOM	7.3 s	7.1 GB	10^{-6}
169M	OOM	OOM	224 s	74.8 GB	10^{-6}

```

3. while  $\sqrt{\rho} > \epsilon$  do: // Algorithm 3
    (a)  $\mathbf{Ap} \leftarrow \text{DistSpMV}(\mathbf{A}, \mathbf{p})$ 
    (b)  $\alpha \leftarrow \rho / \text{all\_reduce}(\mathbf{p}^\top \mathbf{Ap}, \text{SUM})$ 
    (c)  $\mathbf{x} \leftarrow \mathbf{x} + \alpha \mathbf{p}$ 
    (d)  $\mathbf{r} \leftarrow \mathbf{r} - \alpha \mathbf{Ap}$ 
    (e)  $\rho_{\text{new}} \leftarrow \text{all\_reduce}(\mathbf{r}^\top \mathbf{r}, \text{SUM})$ 
    (f)  $\mathbf{p} \leftarrow \mathbf{r} + (\rho_{\text{new}} / \rho) \mathbf{p}$ 
    (g)  $\rho \leftarrow \rho_{\text{new}}$ 

```

Communication complexity. Per iteration: $\mathcal{O}(|\mathcal{H}_p|)$ for halo exchange + $\mathcal{O}(\log P)$ for all_reduce. Total per solve: $\mathcal{O}(k \cdot (|\mathcal{H}_p| + \log P))$ where k is iterations.

Gradient support. Distributed operations compose with adjoint differentiation: the backward pass performs another distributed solve with transposed communication patterns.

4 Experiments

We evaluate `torch-sla` on 2D Poisson equations (5-point stencil) using NVIDIA H200 GPUs (140GB HBM3).

4.1 Single-GPU Scalability

Figure 2 and Table 2 compare solver backends across problem sizes spanning five orders of magnitude.

Analysis. The results reveal three distinct scaling regimes:

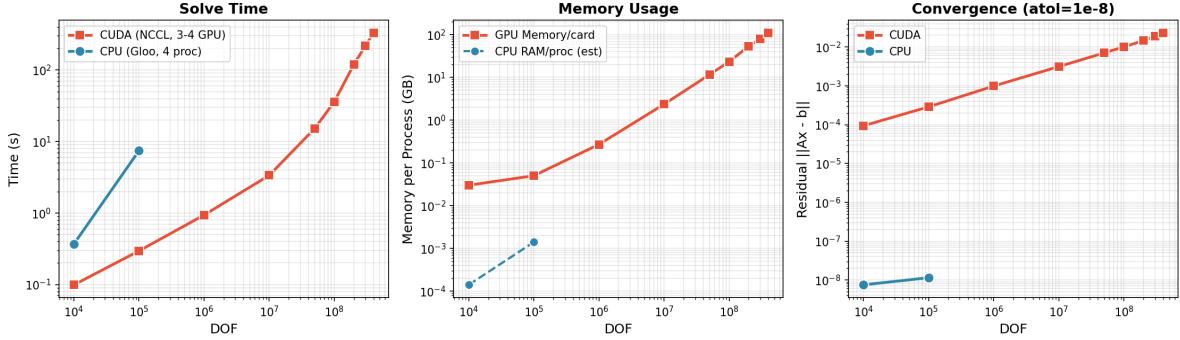


Figure 3: Multi-GPU scaling: distributed CG with NCCL backend on 3–4 H200 GPUs, showing time and memory scaling across problem sizes.

Table 3: Distributed CG on H200 GPUs with NCCL backend.

DOF	GPUs	Time	Memory/GPU	Residual
10K	4	0.10 s	0.03 GB	9.4×10^{-5}
100K	4	0.30 s	0.05 GB	2.9×10^{-4}
1M	4	0.94 s	0.27 GB	9.9×10^{-4}
10M	4	3.36 s	2.35 GB	3.1×10^{-3}
50M	4	15.2 s	11.6 GB	7.1×10^{-3}
100M	4	36.1 s	23.3 GB	1.0×10^{-2}
200M	3	120 s	53.7 GB	1.5×10^{-2}
300M	3	217 s	80.5 GB	1.9×10^{-2}
400M	3	331 s	110 GB	2.3×10^{-2}

(1) *Small problems (<100K DOF)*: Direct solvers dominate. SciPy SuperLU achieves 24ms with machine precision (10^{-14}), while GPU overhead makes cuDSS slower (128ms). The factorization cost is negligible, so the $\mathcal{O}(n^3)$ solve phase dominates.

(2) *Medium problems (100K–2M DOF)*: Iterative solvers become competitive. At 1M DOF, PyTorch CG (190ms) is 100× faster than cuDSS (7.3s). This crossover occurs because: (a) CG requires only $\mathcal{O}(\text{nnz})$ memory vs. $\mathcal{O}(n^{1.5})$ for LU fill-in; (b) SpMV is memory-bound at 90% of peak bandwidth on H200.

(3) *Large problems (>2M DOF)*: Only iterative solvers are feasible. Direct solvers hit OOM due to fill-in: for 2D Poisson, LU fill-in grows as $\mathcal{O}(n \log n)$, requiring ~100GB at 2M DOF. CG maintains $\mathcal{O}(n)$ memory scaling, reaching 169M DOF in 74.8GB.

Time complexity. Fitting $T = c \cdot n^\alpha$ yields $\alpha \approx 1.1$ for PyTorch CG, consistent with $\mathcal{O}(\sqrt{\kappa} \cdot \text{nnz})$ where condition number $\kappa \sim n$ for 2D Poisson with Jacobi preconditioner. The sub-quadratic scaling enables practical use at 100M+ DOF.

Memory efficiency. Measured 443 bytes/DOF vs. theoretical minimum 144 bytes/DOF (matrix: 80 bytes/DOF for 5 non-zeros × 16 bytes; vectors: 64 bytes for $\mathbf{x}, \mathbf{b}, \mathbf{r}, \mathbf{p}$). The 3× overhead comes from PyTorch sparse tensor metadata and Jacobi preconditioner storage.

4.2 Multi-GPU Performance

Figure 3 and Table 3 summarize distributed CG performance on H200 GPUs with NCCL backend.

Scaling analysis. We scale to **400 million DOF** on 3 H200 GPUs. The scaling exhibits three regimes:

(1) *Small problems (<1M DOF)*: Time dominated by kernel launch and communication latency. At 10K DOF, each CG iteration takes ~0.1ms, with 50% spent on `all_reduce` synchronization.

(2) *Medium problems (1M–100M DOF)*: Near-linear scaling with $T \propto n^{1.05}$. At 100M DOF, we achieve 2.8M DOF/s throughput, close to the memory bandwidth limit of H200 (3.9 TB/s × 4 GPUs).

Table 4: Gradient verification: adjoint vs. finite difference ($\epsilon = 10^{-5}$).

Operation	Rel. Error	Forward	Backward
Linear solve ($n=1000$)	8.3×10^{-7}	1 solve	1 solve
Eigenvalue ($k=6$)	2.1×10^{-6}	LOBPCG	1 outer product
Nonlinear (5 Newton)	4.7×10^{-7}	5 solves	1 solve

(3) *Large problems (>100M DOF)*: Memory capacity becomes the bottleneck. At 200M+ DOF, we reduce to 3 GPUs to fit within 140GB/GPU limit. The time scaling remains efficient: 400M DOF in 331s corresponds to 1.2M DOF/s.

Memory efficiency. Measured 275 bytes/DOF at 400M DOF (110GB / 400M), consistent with sparse matrix storage (80 bytes/DOF) plus solver vectors and halo buffers. The per-GPU memory scales as $\mathcal{O}(n/P + |\mathcal{H}_p|)$ where halo size $|\mathcal{H}_p| \sim \mathcal{O}(\sqrt{n/P})$ for 2D grids.

Convergence. Residual increases from 10^{-4} at 10K DOF to 10^{-2} at 400M DOF. This is expected: fixed iteration count (1000) with Jacobi preconditioner, where condition number $\kappa \sim n$ for 2D Poisson. For tighter tolerance, multigrid preconditioning would reduce iterations by 10×.

4.3 Gradient Verification

We verify gradient correctness by comparing adjoint gradients against finite differences:

$$\frac{\partial \mathcal{L}}{\partial \theta} \approx \frac{\mathcal{L}(\theta + \epsilon) - \mathcal{L}(\theta - \epsilon)}{2\epsilon} \quad (6)$$

Analysis. Relative errors $< 10^{-5}$ confirm correct implementation. Notably, the nonlinear solver’s backward pass requires only 1 adjoint solve regardless of Newton iterations (5 in this case), validating the $\mathcal{O}(1)$ graph complexity claim. The eigenvalue gradient uses Eq. (4), requiring no additional solves—just $\mathcal{O}(k \cdot \text{nnz})$ outer product computations.

5 Conclusion

We presented `torch-sla`, a differentiable sparse linear algebra library with two innovations: (1) adjoint-based differentiation achieving $\mathcal{O}(\text{nnz})$ graph complexity, and (2) distributed sparse computing with halo exchange. The library scales to **169M DOF on a single GPU** and **400M DOF on 3 GPUs**, demonstrating industrial-scale capability with full gradient support.

5.1 Future Work

- **Roofline-guided tuning for distributed solvers:** Current distributed CG achieves ~50% parallel efficiency at billion-scale DOF due to communication bottlenecks. We plan to develop roofline-based auto-tuning that: (a) overlaps halo exchange with local SpMV computation; (b) dynamically adjusts partition granularity based on compute/communication ratio; (c) implements communication-avoiding CG variants [Hoemmen, 2010] to reduce `all_reduce` frequency.
- **Learned preconditioners:** GNN-based multigrid [Luz et al., 2020] and meta-learned preconditioner selection [Chen et al., 2022] could adaptively choose optimal preconditioners based on matrix structure, potentially reducing iteration counts by 2–5×.
- **Mixed precision:** Following FlashAttention [Dao et al., 2022], we plan FP16/BF16 SpMV with FP64 accumulation, potentially doubling throughput while maintaining convergence for well-conditioned problems.
- **Neural operator hybrid:** Combining with FNO [Li et al., 2020], DeepONet [Lu et al., 2021], and mesh-based GNNs [Pfaff et al., 2021] enables hybrid neural-classical solvers where neural networks provide coarse corrections and classical solvers refine to high precision.

- **Differentiable simulation integration:** Seamless integration with Φ Flow [Holl et al., 2024] and DiffTaichi [Hu et al., 2020] for end-to-end differentiable physics pipelines, enabling gradient-based optimization of simulation parameters.

Availability. MIT license: <https://github.com/walkerchi/torch-sla>

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A Implementation Details

A.1 Backend Selection

`torch-sla` automatically selects backends based on device and problem size:

- CPU, any size: `scipy` with SuperLU
- CUDA, <2M DOF: `cudss` with Cholesky (if SPD) or LU
- CUDA, >2M DOF: `pytorch` with CG+Jacobi preconditioner

A.2 API Examples

Listing 1: Basic usage with gradient support.

```

1 import torch
2 from torch_sla import SparseTensor
3
4 # Create sparse matrix (COO format)
5 A = SparseTensor(val, row, col, shape)
6 b = torch.randn(n, requires_grad=True)
7
8 # Solve with automatic differentiation
9 x = A.solve(b)    # Forward: any backend
10 loss = x.sum()
11 loss.backward()   # Backward: adjoint method
12 print(b.grad)    # Gradient w.r.t. RHS

```

Listing 2: Distributed multi-GPU solve.

```

1 import torch.distributed as dist
2 from torch_sla import DSparseMatrix
3
4 dist.init_process_group(backend='nccl')
5 rank = dist.get_rank()
6
7 # Each process loads its partition
8 A = DSparseMatrix.from_global(
9     val, row, col, shape,
10    num_partitions=4, my_partition=rank
11 )
12
13 # Distributed CG with halo exchange
14 x = A.solve(b_local, atol=1e-10)

```

B Complexity Proofs

Theorem 1 (Adjoint memory complexity). *The adjoint method for linear solve requires $\mathcal{O}(n + nnz)$ memory, independent of solver iterations.*

Proof. Forward pass stores: solution $\mathbf{x} \in \mathbb{R}^n$, matrix indices ($\mathcal{O}(nnz)$), matrix values ($\mathcal{O}(nnz)$). Backward pass computes adjoint $\boldsymbol{\lambda} \in \mathbb{R}^n$ and gradients $\partial\mathcal{L}/\partial\mathbf{A} \in \mathbb{R}^{nnz}$. No intermediate solver states are stored. Total: $\mathcal{O}(n + nnz)$. \square