

High Performance Linear System Solvers with Focus on Graph Laplacians

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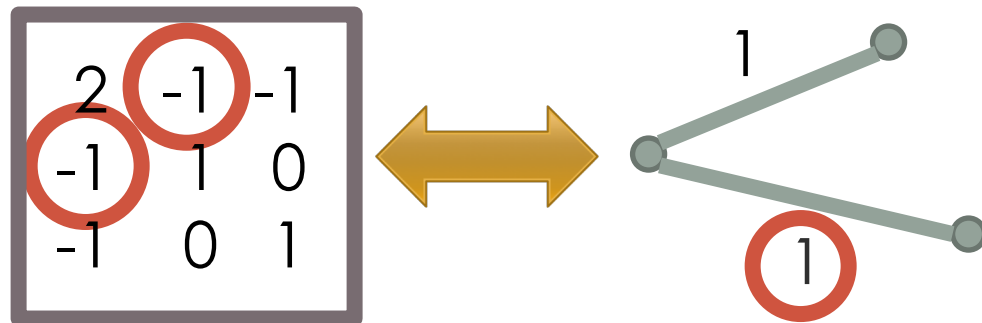
Based on work joint with: Serban Stan, Shen Chen Xu, Saurabh Sawlani,
John Gilbert, Kevin Deweese, Gary Miller, Hui Han Chin

OUTLINE

- **Laplacian solvers and applications**
- Combinatorial preconditioning
- Numerics of tree preconditioners

GRAPH LAPLACIAN MATRIX

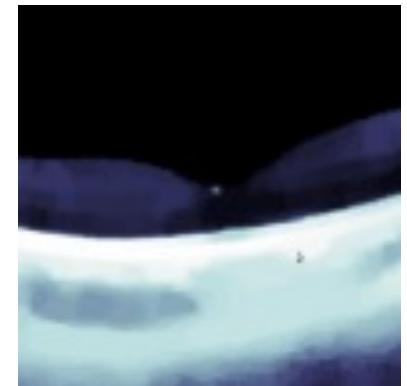
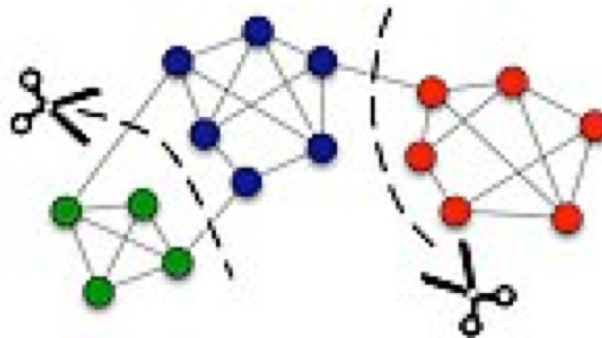
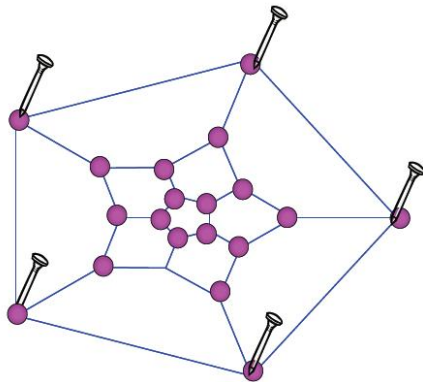
- Diagonal: weighted degrees
- Off-diagonal: -edge weights



FEW ITERATIONS OF $Lx = b$

Spring-mass system / elliptic problems / M matrices

- [Tutte '61]: planar embedding / graph drawing,
- [ZGL '03], [ZHS '05] [KRS '15]: learning/inference

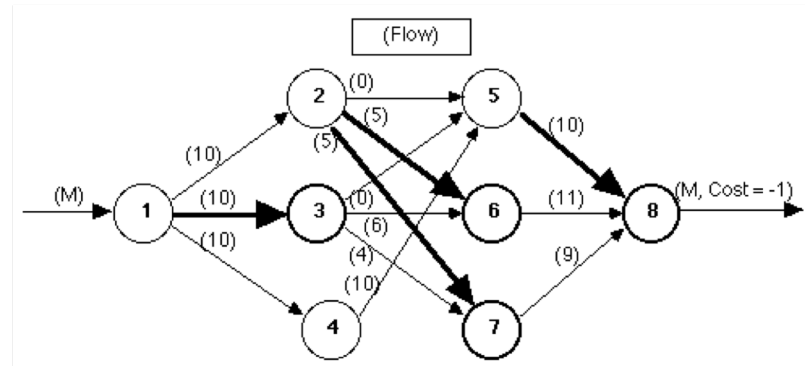
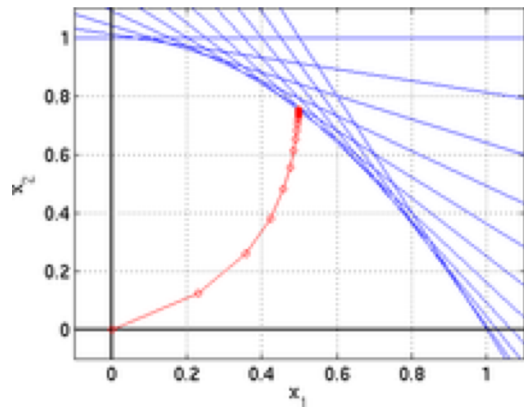


Inverse powering: eigenvectors / heat kernel:

- [AM '85] [OSV '12]: clustering
- [SM '01][KMST '09]: image segmentation

MANY ITERATIONS OF $\mathbf{Lx} = \mathbf{b}$

[Karmarkar, Ye, Renegar, Nesterov, Nemirovski ...]:
convex optimization via. solving $O(m^{1/2})$ linear systems



[DS `08][CKMST `11][LS `14][AKPS `19][APS`19][AS `20]:
graph problems \rightarrow Laplacian linear systems

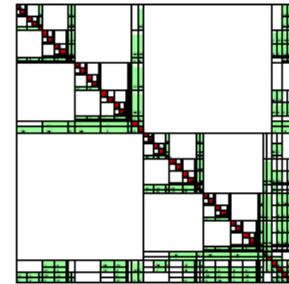
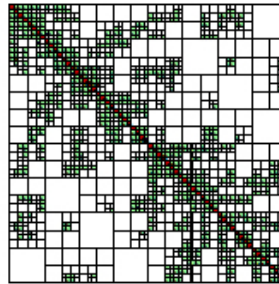
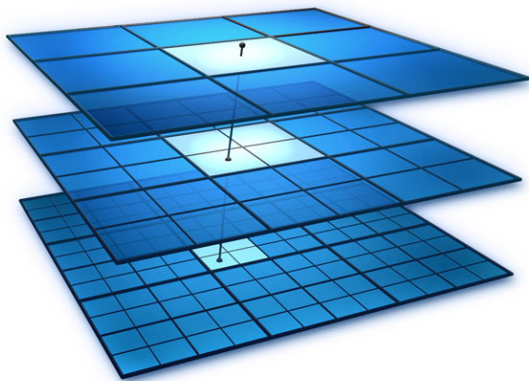
LINEAR SYSTEMS SOLVERS

- Matrix multiplication: $O(n^{2.372864\dots})$
- Conjugate gradient: $O(nnz \cdot k^{1/2})$
where k is condition number

Open: provably faster solver for $\text{poly}(n)$ conditioned sparse ($O(n)$ nonzero) systems.
[Zhang '18]: structure often don't help

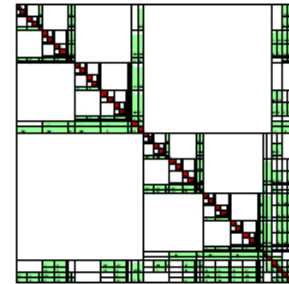
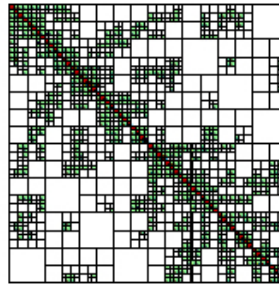
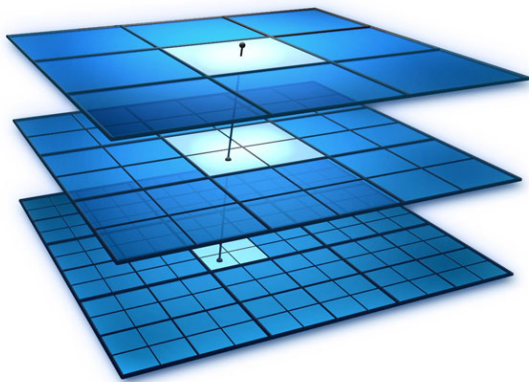
$\mathbf{Lx} = \mathbf{b}$ in Practice

- Scientific computing: multigrid ‘works’ for 10^9 nonzeros
- MATLAB: `pcg(L, ichol(L), b, ϵ)` ‘works’ for 10^6 nonzeros



$\mathbf{Lx} = \mathbf{b}$ in Practice

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‘works’: gradual numerical convergence

NUMERICAL METHODS

Gradual convergence to solutions

Simplest: $\mathbf{x} \leftarrow \mathbf{x} + \theta(\mathbf{Ax} - \mathbf{b})$

Fixed point: $\mathbf{Ax} = \mathbf{b}$

Better schemes: conjugate
gradient, accelerated methods

NUMERICAL METHODS

Gradual convergence to solutions

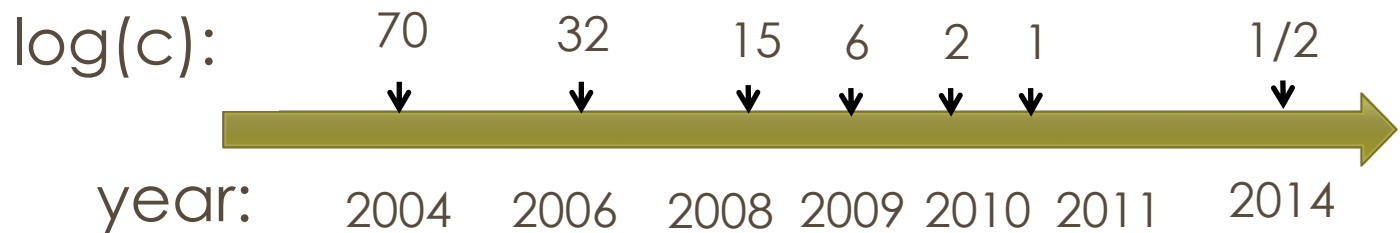
Preconditioned: $\mathbf{x} \leftarrow \mathbf{x} + \theta \mathbf{B}^{-1}(\mathbf{Ax} - \mathbf{b})$

Want: \mathbf{B} that's close to \mathbf{A} , but computationally less expensive:

- Jacobi: $\mathbf{B} = \text{Diag}(\mathbf{A})$
- Gauss Siedel: $\mathbf{B} = \text{TriU}(\mathbf{A})$
- Incomplete Cholesky: drop small entries during sparse elimination

COMBINATORIAL PRECONDITIONING

- [Vaidya `89]: use graph theory to build preconditioners for \mathbf{L}
- [ST`04]: $O(m \log^c n \log(1/\epsilon))$ time
- 2004 – 2014: c halved every 2 years

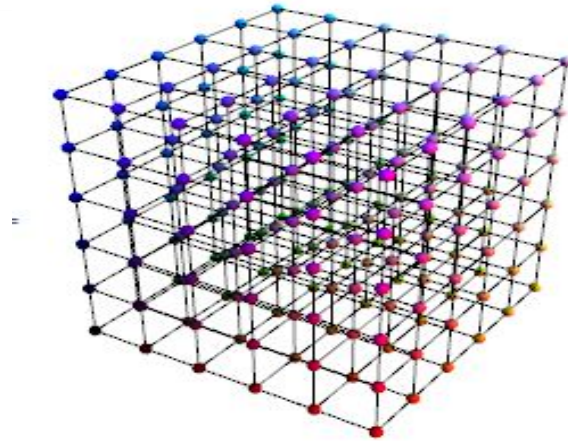


Most recent: [KS `16] showed randomized incomplete Cholesky provably works for \mathbf{L}

COMPARE? NEW BENCHMARKS:

Structured graphs

- Grids / cubes
- Cayley graphs
- Graph products

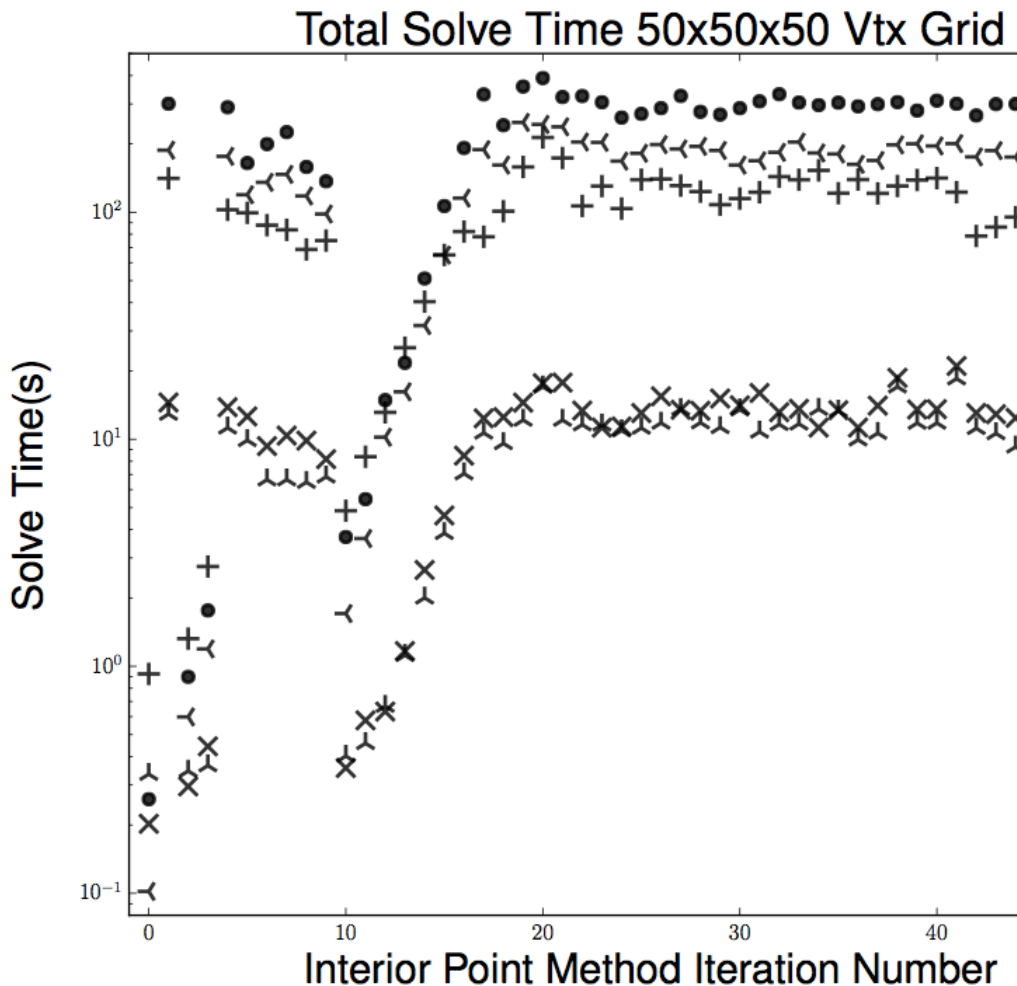


Hard graph problems

- Maxflow problems from DIMACS implementation challenges
- Linear systems arising from second-order optimization (IPM)

[KRS'15] + DIFFERENT SOLVERS

Disclaimer: this behavior depend heavily on IPM implementation / numerics / termination conditions



README file at
<https://github.com/sachdevasushant/Isotonic>

we suggest rerunning
the program a few
times and / or using a
different solver.

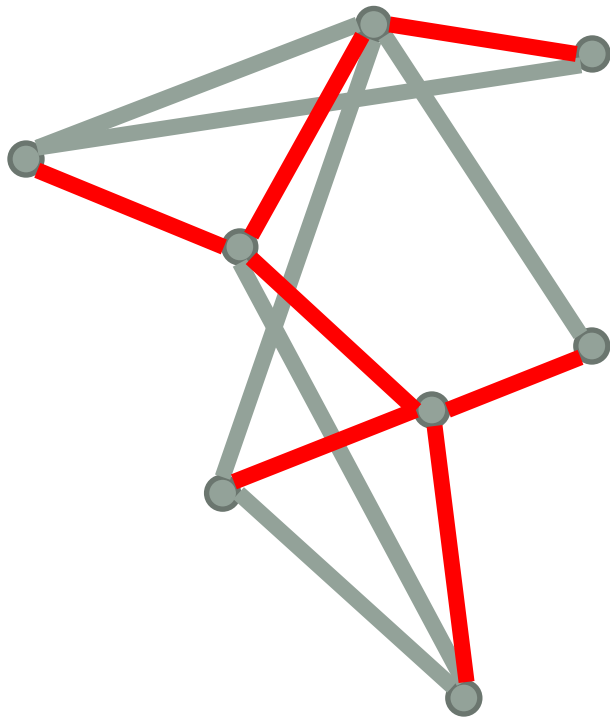
●	Jacobi
↖	SGS
↗	ILU
×	MST
+	AMG

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- Numerics of tree preconditioners

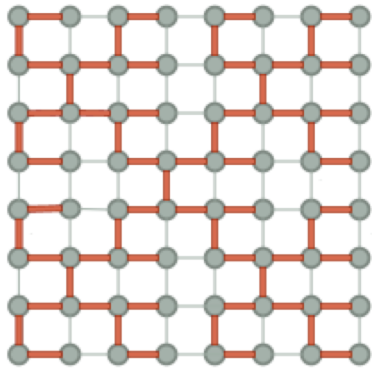
TREE BASED PRECONDITIONERS

Gradually transform a tree-based solution to a solution on the entire graph

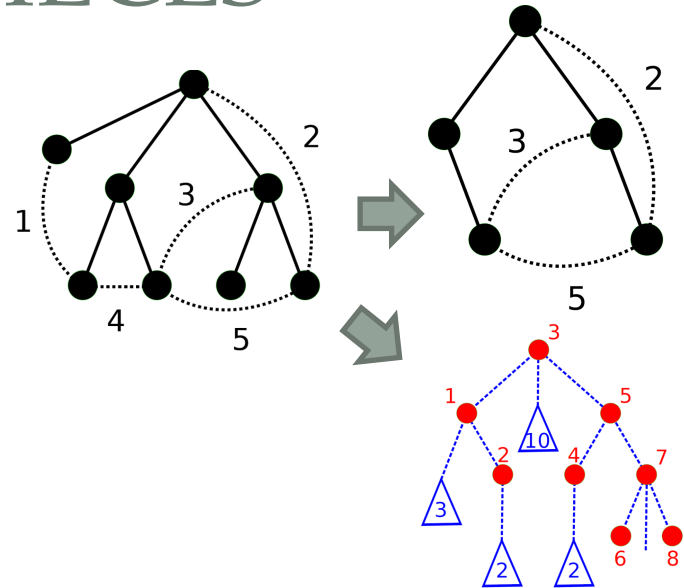
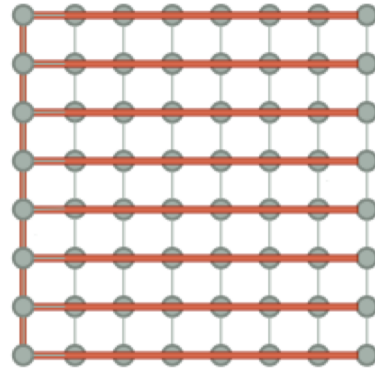


Method	Cycle Toggle	Precondition
Cost / Iter	$\log n$	$m + (m/k)^2$
# Iters	$m \log^{1/2} n \log(1/\epsilon)$	$k^{1/2} \log(1/\epsilon)$
Related to	SGD	Grad. descent
Primitives	Data structures	Mat-Vec

MOVING PIECES



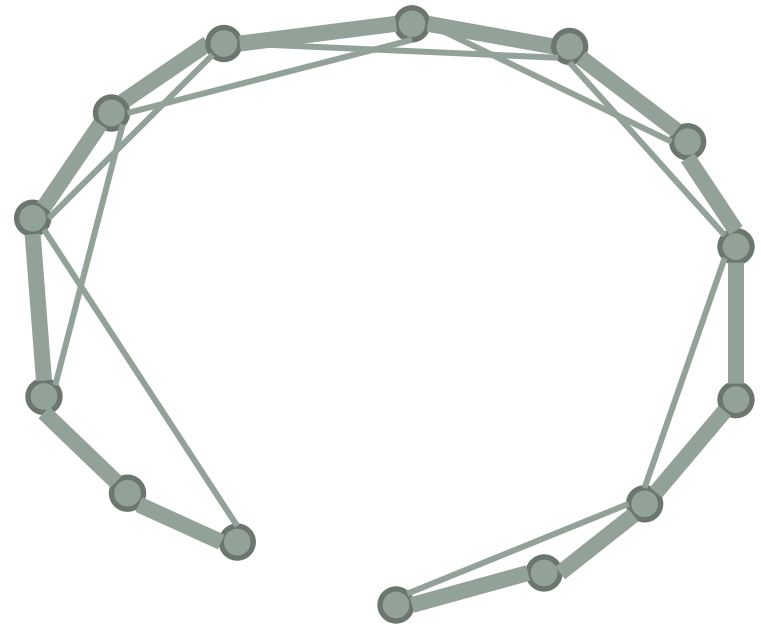
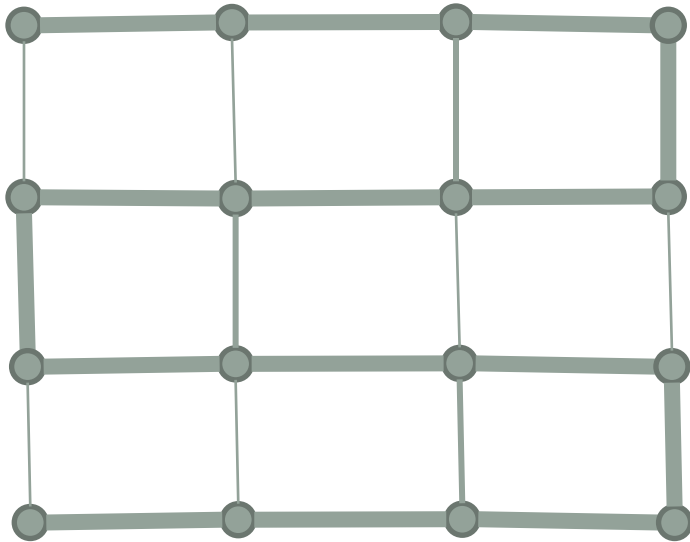
VS



- Trees: MST / bottom-up / top-down / adaptive
- Numerics: batched / local, accelerated / CG
- Memory layout, recursive vs. iterative

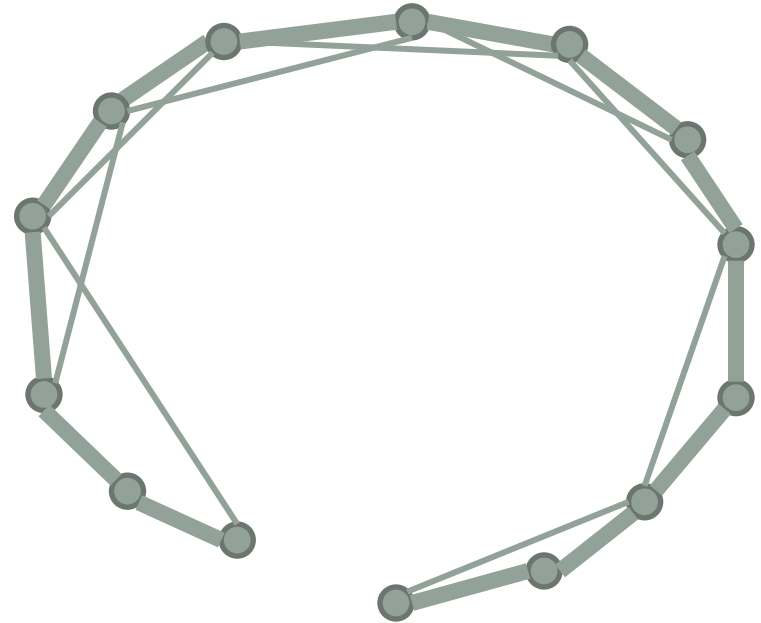
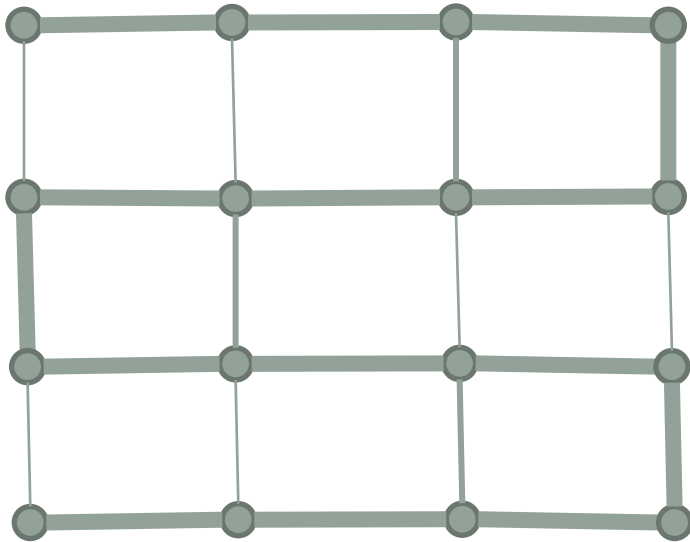
[DGMPXX CSC`16]: HEAVY PATHS

Pick a Hamiltonian path, weight all other edges so each has stretch 1



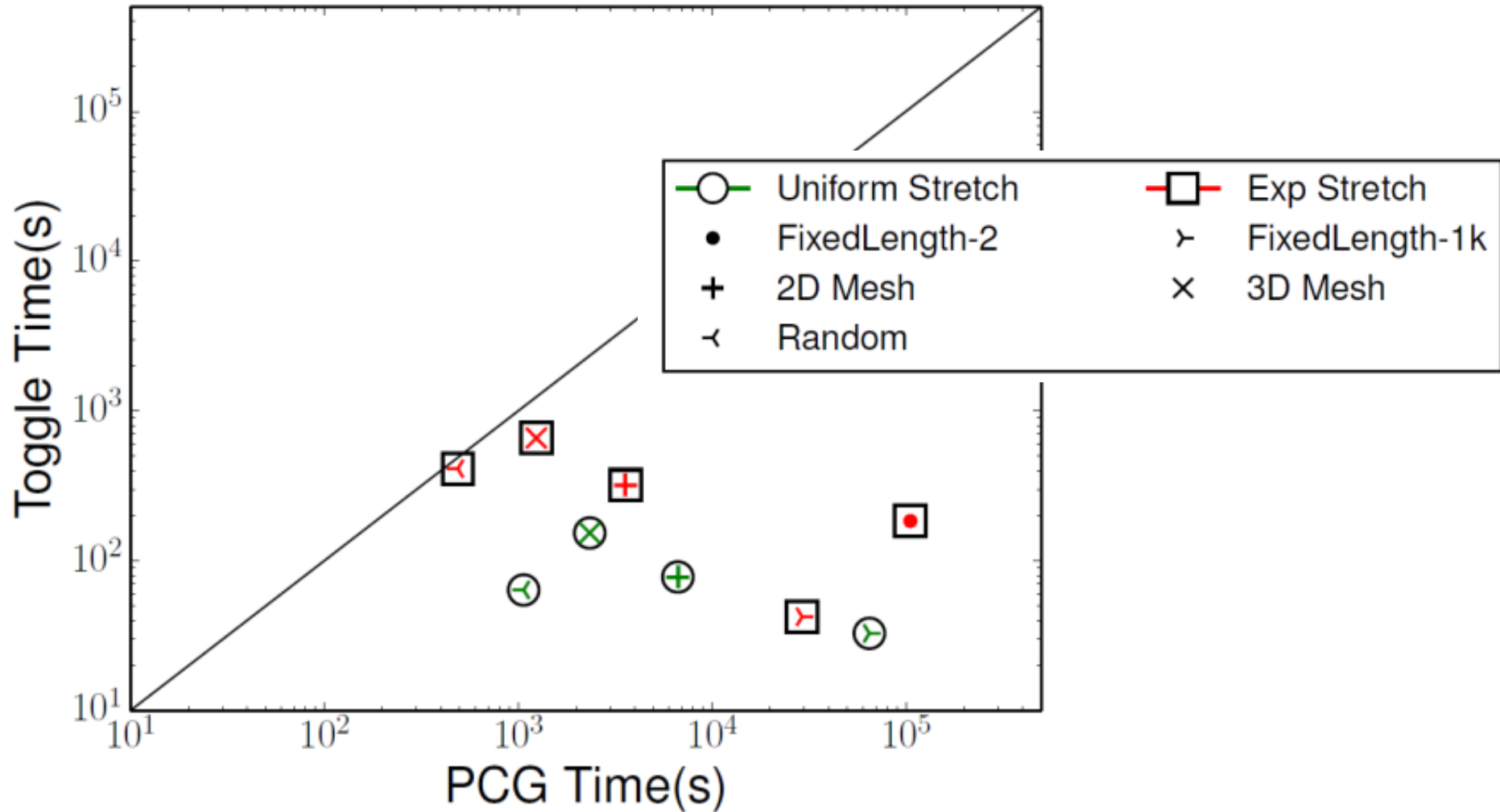
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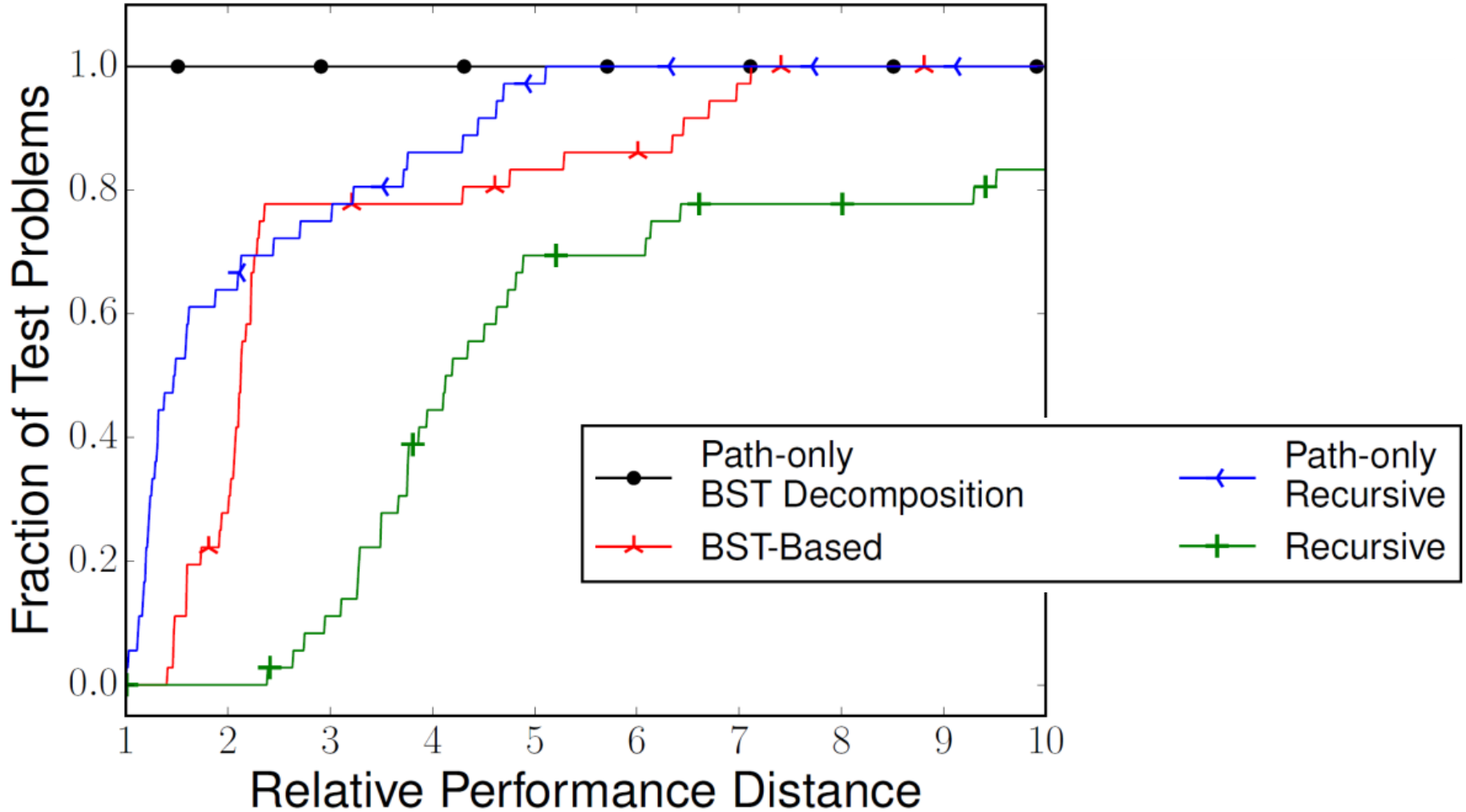
- Bad case for PCG,
- 'easy' for tree data structures

DOING BETTER THAN CG



<https://arxiv.org/abs/1609.02957>
<https://github.com/sxu/cycleToggling>

COMPARISONS OF GRAPHS \rightarrow TREES

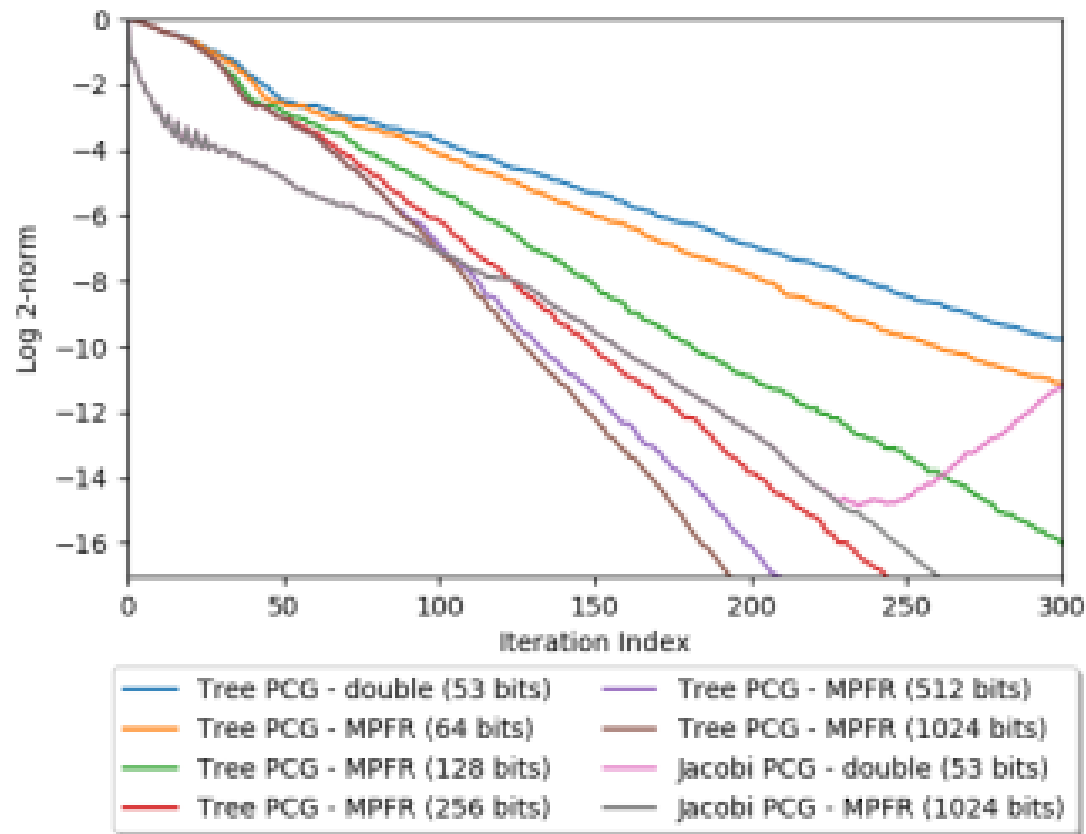


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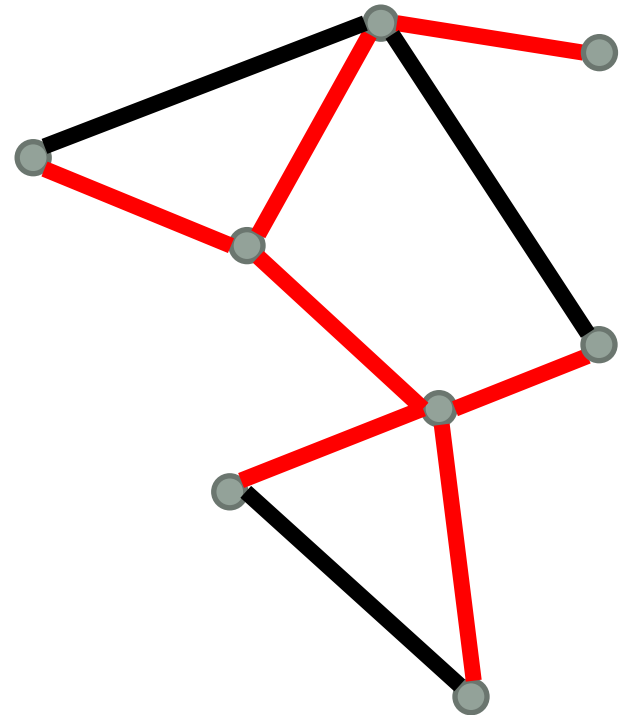
[DPSX CSC'20] NUMERICAL ISSUES



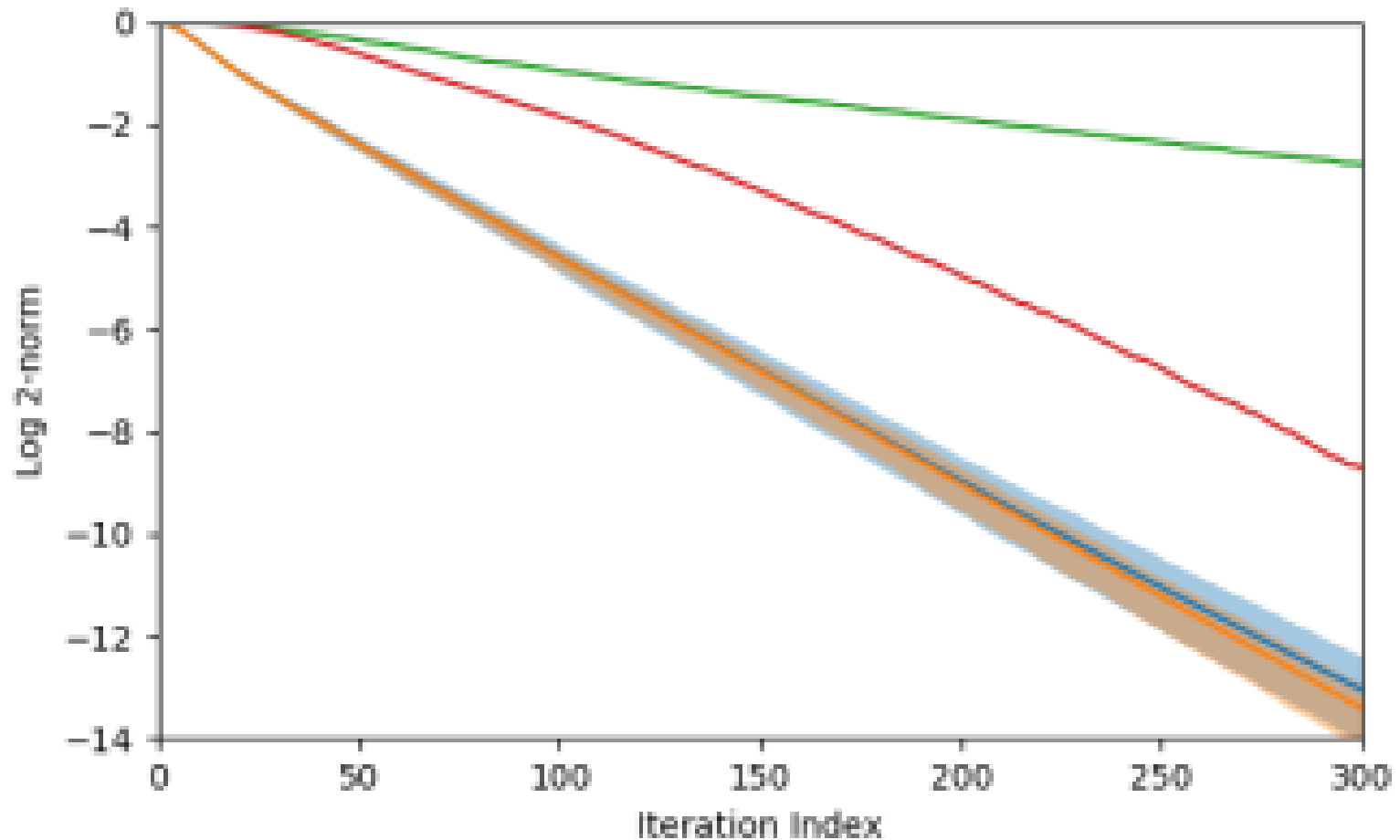
CG with a low-stretch tree as preconditioner

ONE FIX: BATCHED PROCESSING

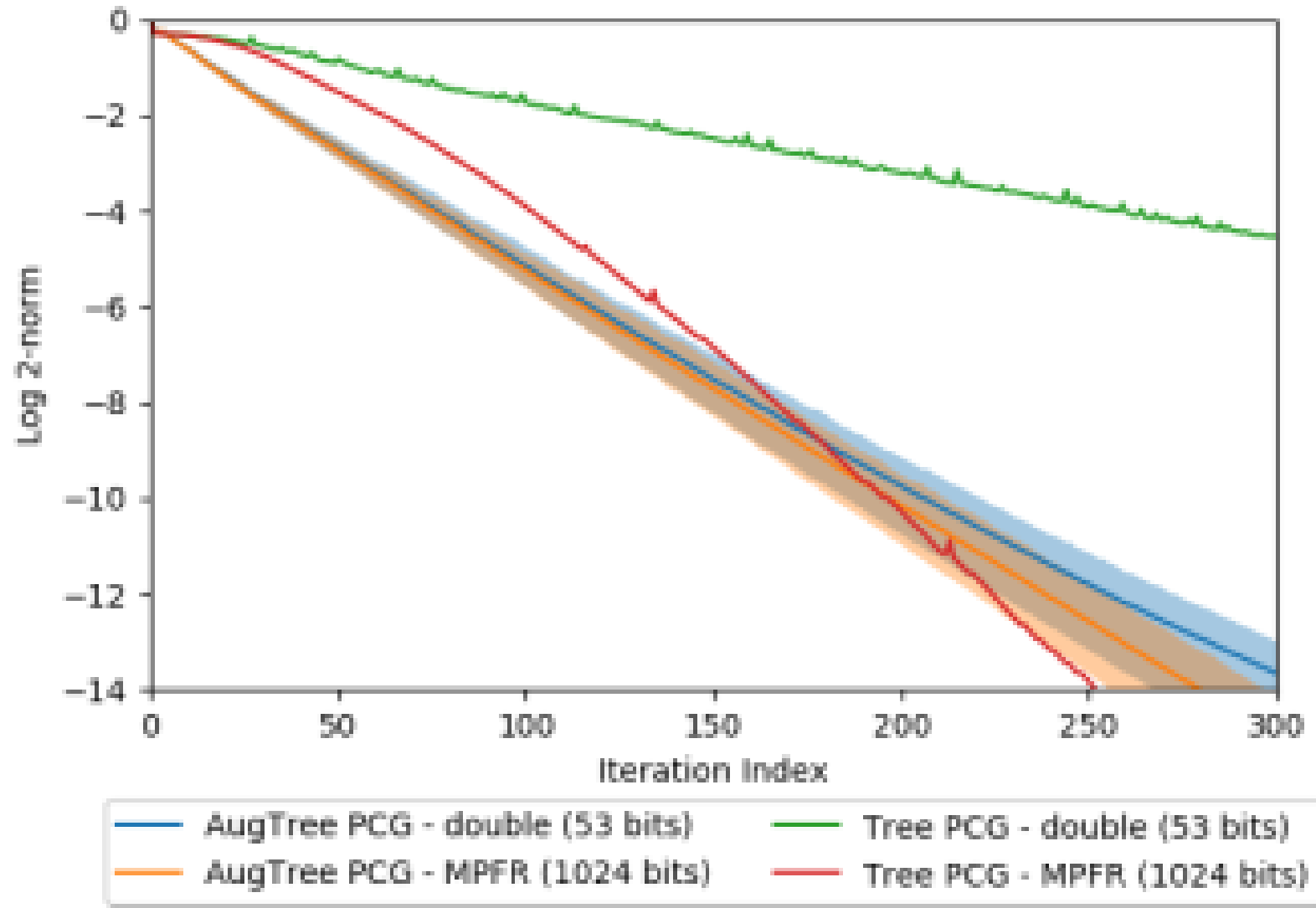
- Add some edges to a tree to form a 'batched' preconditioner
- Use direct methods to factorize preconditioner explicitly



COMPARISON ON 3D CUBE



COMPARISON ON IPM MATRIX



EVALUATING LAPLACIAN SOLVERS

- We have a much better idea of what are the instances to test on now:
 - Instances that are numerically close to paths
 - Weighted grid graphs
 - Inner loops of optimization algorithms
 - [Deweese-Gilbert '18]: evolve instances
- Benchmark incomplete Cholesky?
- Measuring numerical behaviors?
- Benchmark w.r.t. applications: ground-truth instead of residual error?