Addressing the Communication Bottleneck:
Towards a Modular Precision Ecosystem for High Performance Computing

A Structured Approach for Programming Extreme-Scale and Heterogeneous Systems (EPIGRAM-HS project)
Zurich, September 9th, 2019

Hartwig Anzt, Terry Cojean, Goran Flegar, Thomas Grűtzmacher, Pratik Nayak, Tobias Ribizel
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Pratik Nayak


Tobias Ribizel

Where do we stand?

OAK RIDGE National Laboratory | LEADERSHIP COMPUTING FACILITY

summit

- Node: 2 IBM POWER9 + 6 NVIDIA V100 GPUs
- 4,608 nodes, 9,216 IBM Power9 CPUs
- 27,648 V100 GPUs (8 TFLOPs / GPU)
- Peak performance of **200 Pflop/s** for modeling & simulation
- Peak performance of **3.3 Eflop/s** (10^18) for 16 bit floating point used in data analytics and artificial intelligence

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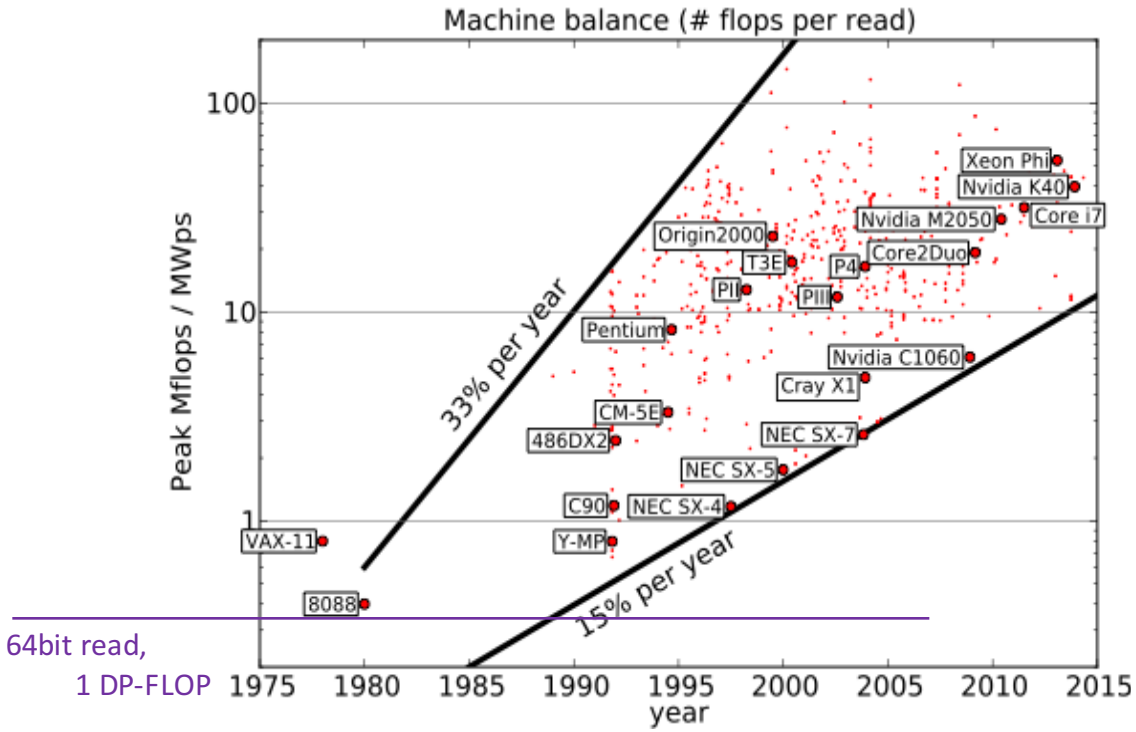

John D. McCalpin (TACC)

- Compute power (#FLOPs) grows much faster than bandwidth.

"Operations are free, mem access and comm is what counts."

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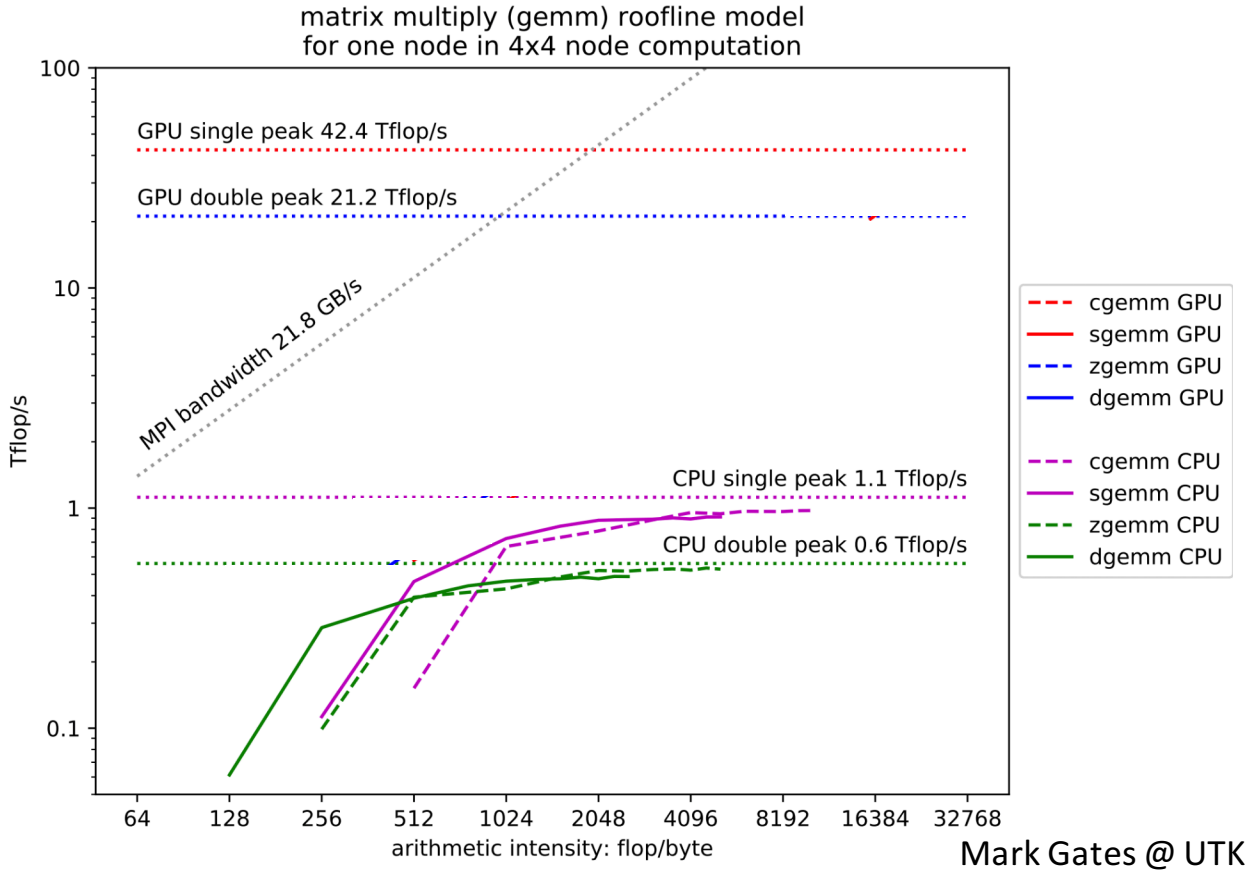
Dense Matrix Operations?

- The inter-node communication is the limiting resource;
- Each node has more computational power than what we can leverage;



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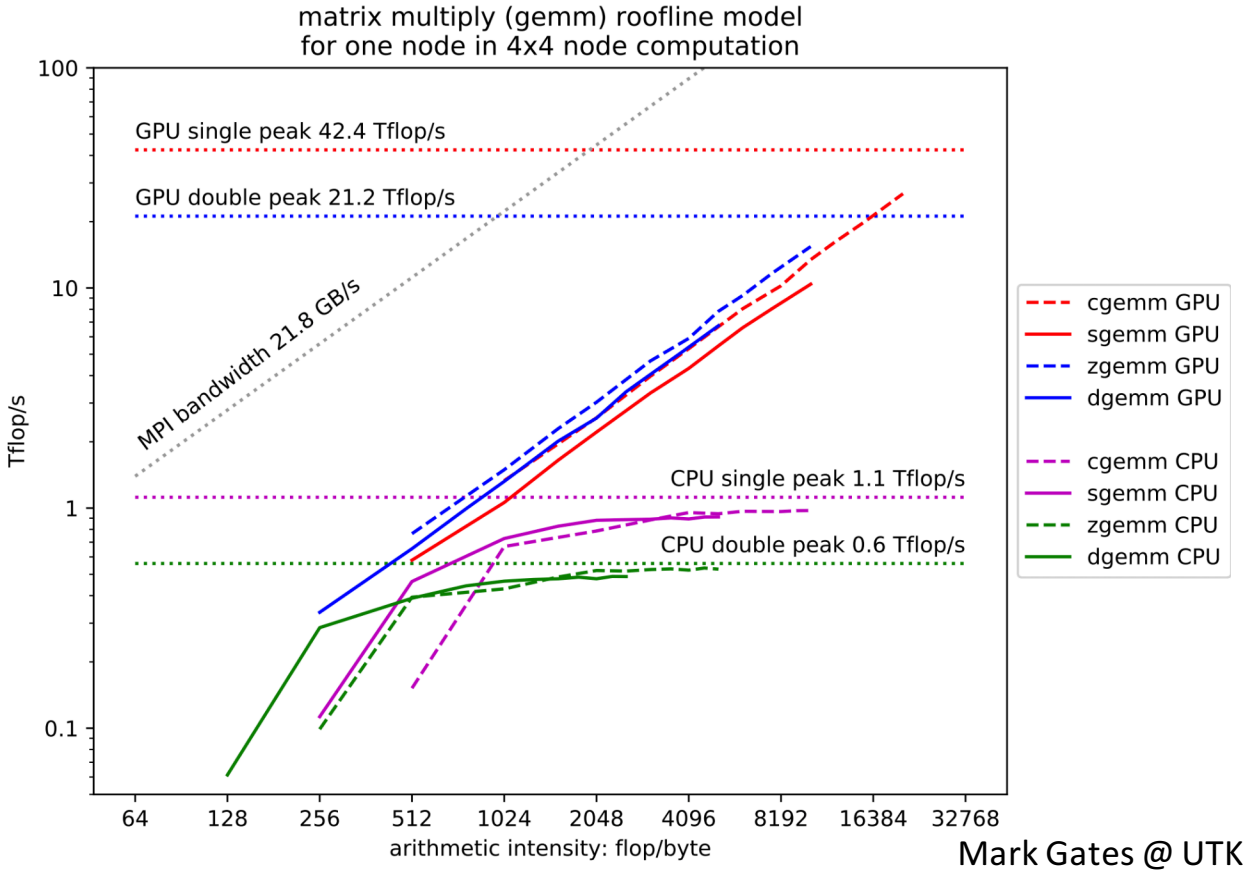

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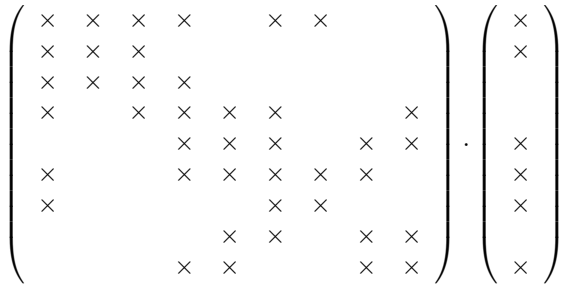
Sparse / Graph Problems?

- ***Sp**arse **M**atrix **V**ector Product* (SpMV) is a central building block;



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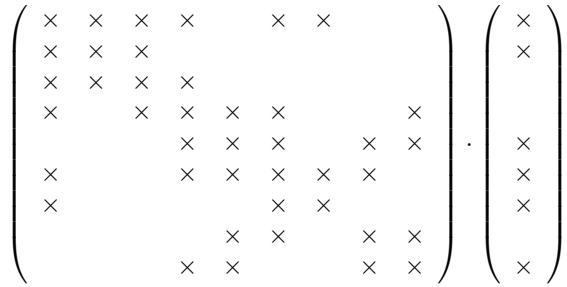
Sparse / Graph Problems?

- ***Sp**arse **M**atrix **V**ector Product* (SpMV) is a central building block;
- It looks like for the test problems at the SuiteSparse Matrix Collection[1], a Multi-node SpMV is slower than a Single-node SpMV;
- The inter-node communication is an order of magnitude slower than the local computations.



[1]SuiteSparse Matrix Collection: https://sparse.tamu.edu/

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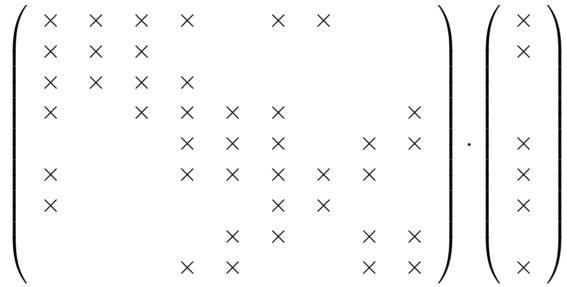

Radically decouple storage format from arithmetic format.

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Radically decouple storage format from arithmetic format.

- The arithmetic operations should use high precision formats natively supported by hardware.
- **Data access** should be as cheap as possible, **reduced precision**.

Challenges when using double precision + IEEE single/half precision:

- Need explicit conversion.
- Data range reduction: protect against under- / overflow.
- Need to duplicate data in memory (half/single/double).

- Better: **Customized Precision Format**

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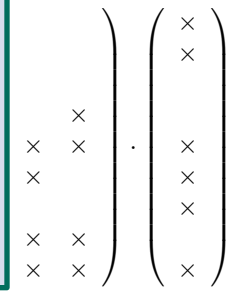

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Use reduced precision for “approximate Operators”

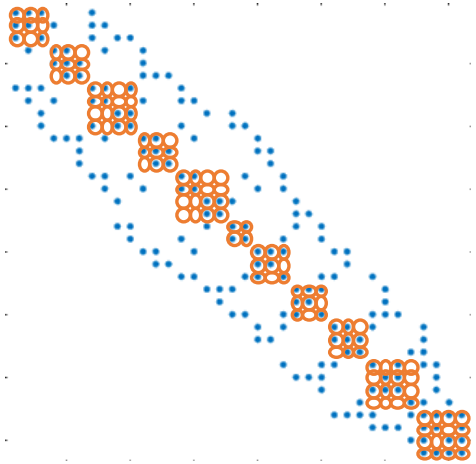
- **Preconditioners for iterative solvers.**
  - Idea: Approximate inverse of system matrix to make the system “easier to solve”: $P^{-1} \approx A^{-1}$

    $\tilde{A} = P^{-1}A\,, \quad \tilde{b} = P^{-1}b\,,$ and we solve $Ax = b \Leftrightarrow \tilde{A}x = \tilde{b}\,.$
- **Why should we store the preconditioner matrix P^{-1} in full (high) precision?**
  - **We have to ensure regularity!** (Reducing precision can turn matrix singular)

- **Jacobi method** based on **diagonal scaling:** $P = diag(A)$

- **Block-Jacobi** is based on **block-diagonal scaling**: $P = diag_B(A)$
  - Large set of small diagonal blocks.
  - Each block corresponds to one (small) linear system.
    - *Larger* blocks typically **improve convergence**.
    - *Larger* blocks make block-Jacobi **more expensive**.

    Extreme case: one block of matrix size.



Block-Jacobi Preconditioning

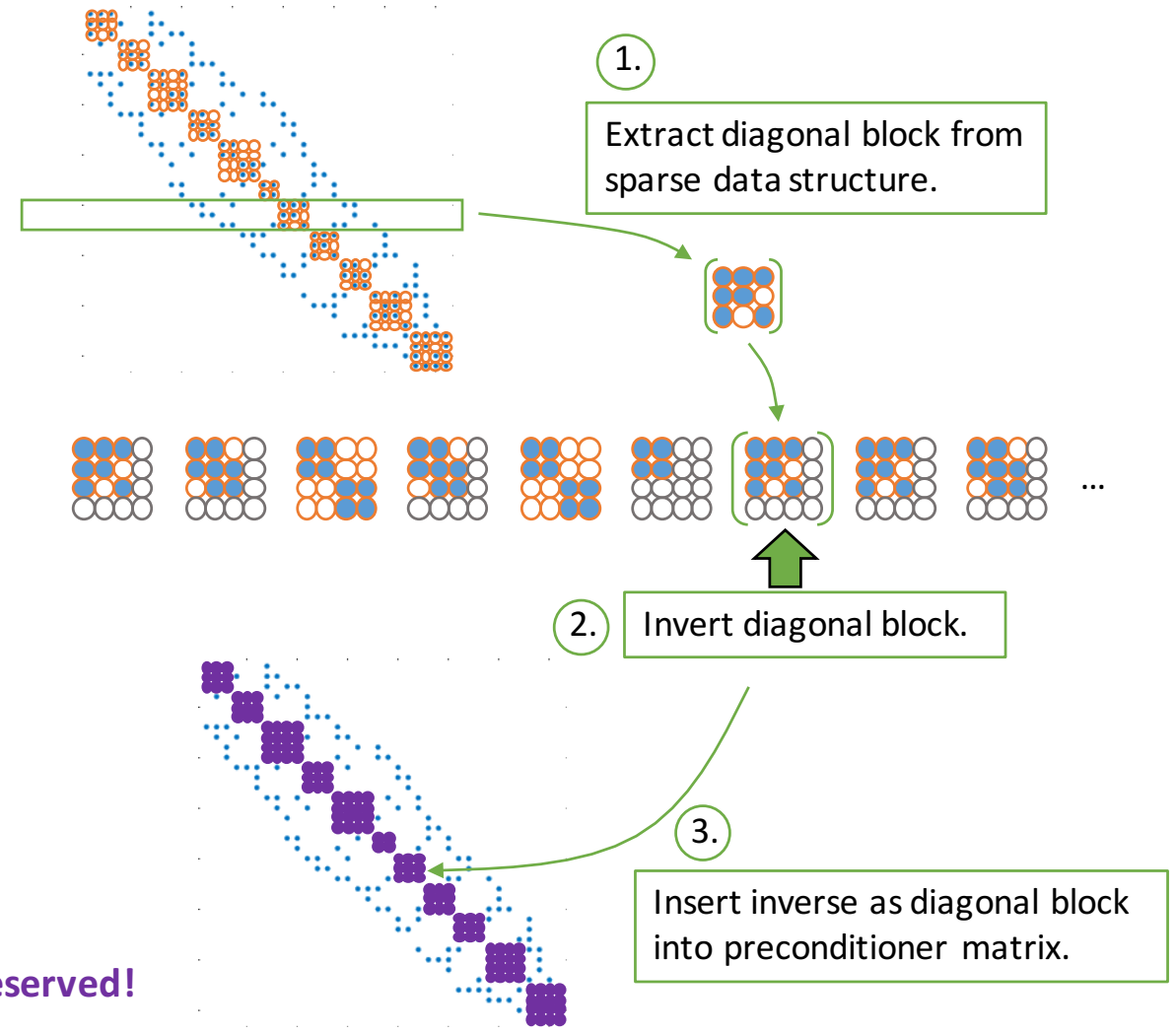
Preconditioner Setup:

- Identify the diagonal blocks $P = diag_B(A)$
- Form the block-Inverse $P^{-1} \approx A^{-1}$

Preconditioner Application:

- Apply the preconditioner in every solver iteration via:

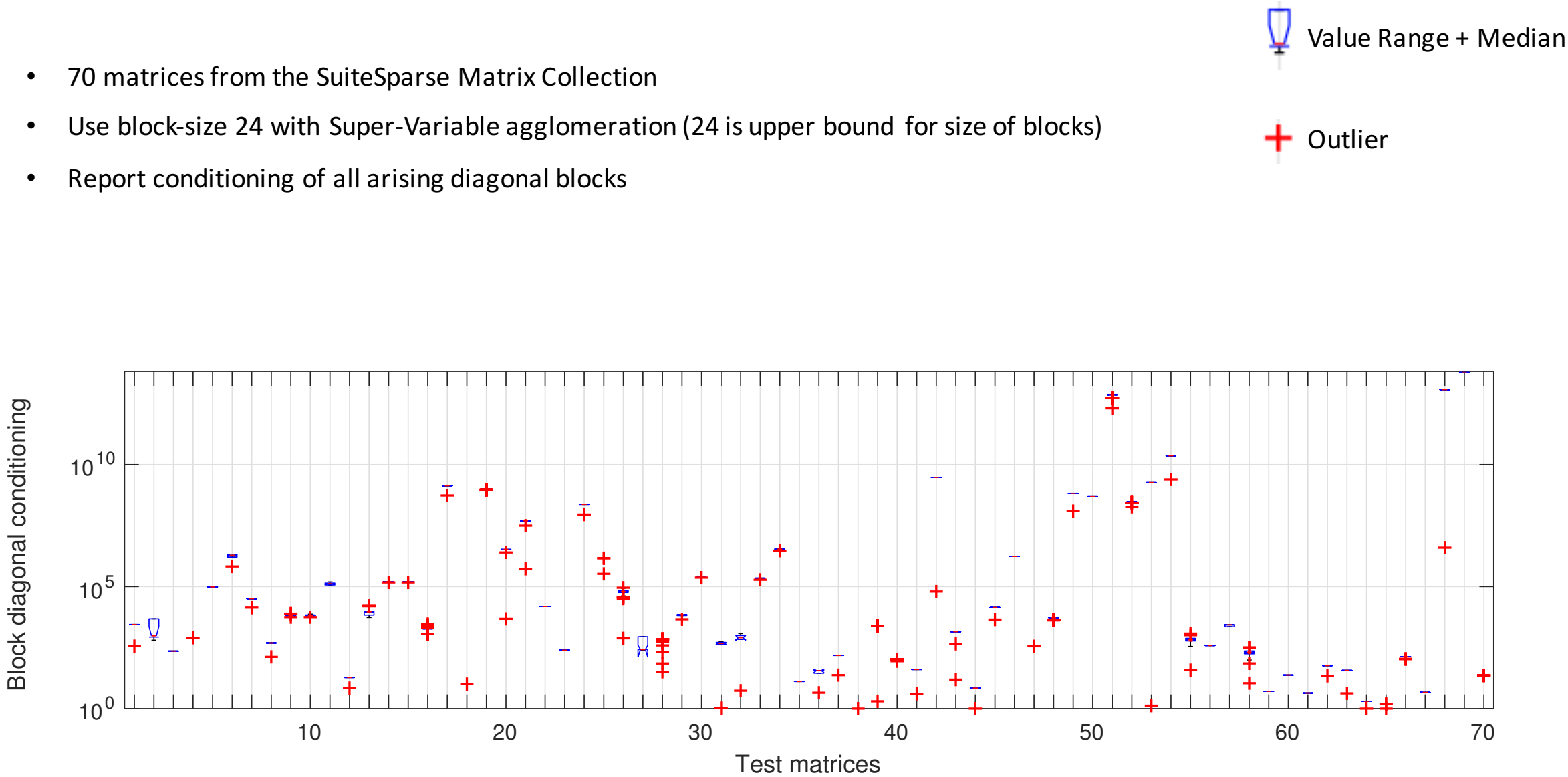
$$y := P^{-1}x$$



We can store diagonal blocks in lower precision, if regularity is preserved!

Adaptive Precision Block-Jacobi Preconditioning

- 70 matrices from the SuiteSparse Matrix Collection
- Use block-size 24 with Super-Variable agglomeration (24 is upper bound for size of blocks)
- Report conditioning of all arising diagonal blocks



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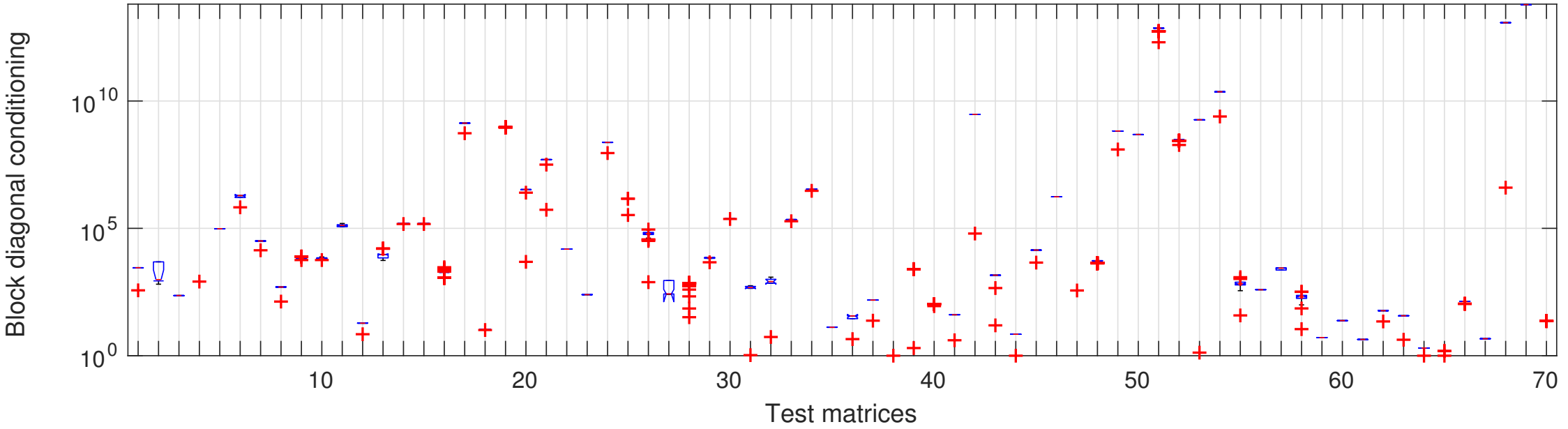
- 70 matrices from the SuiteSparse Matrix Collection
- Use block-size 24 with Super-Variable agglomeration (24 is upper bound for size of blocks)
- Report conditioning of all arising diagonal blocks
- Analyze the impact of storing block-Jacobi in lower precision a top-level Conjugate Gradient solver (CG)



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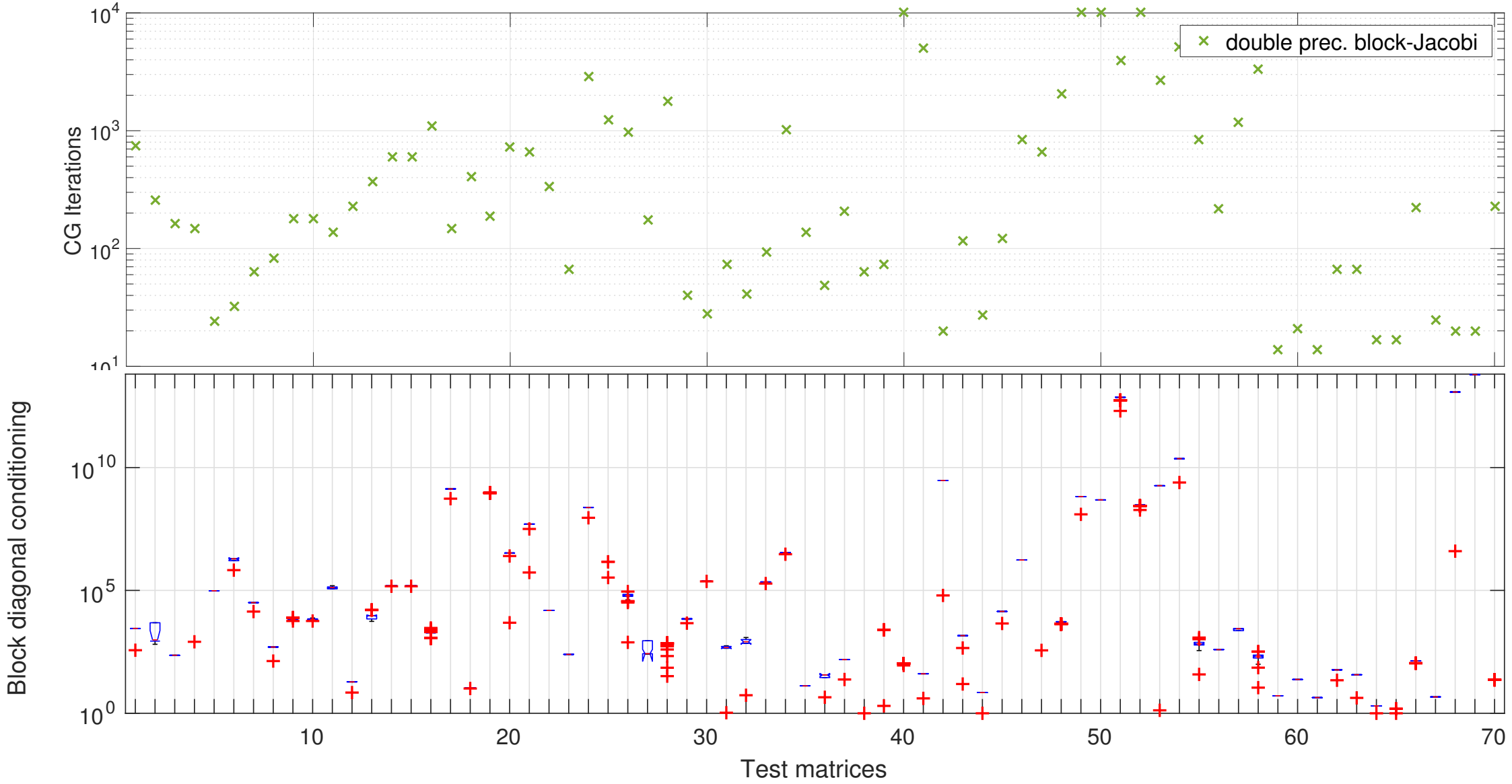

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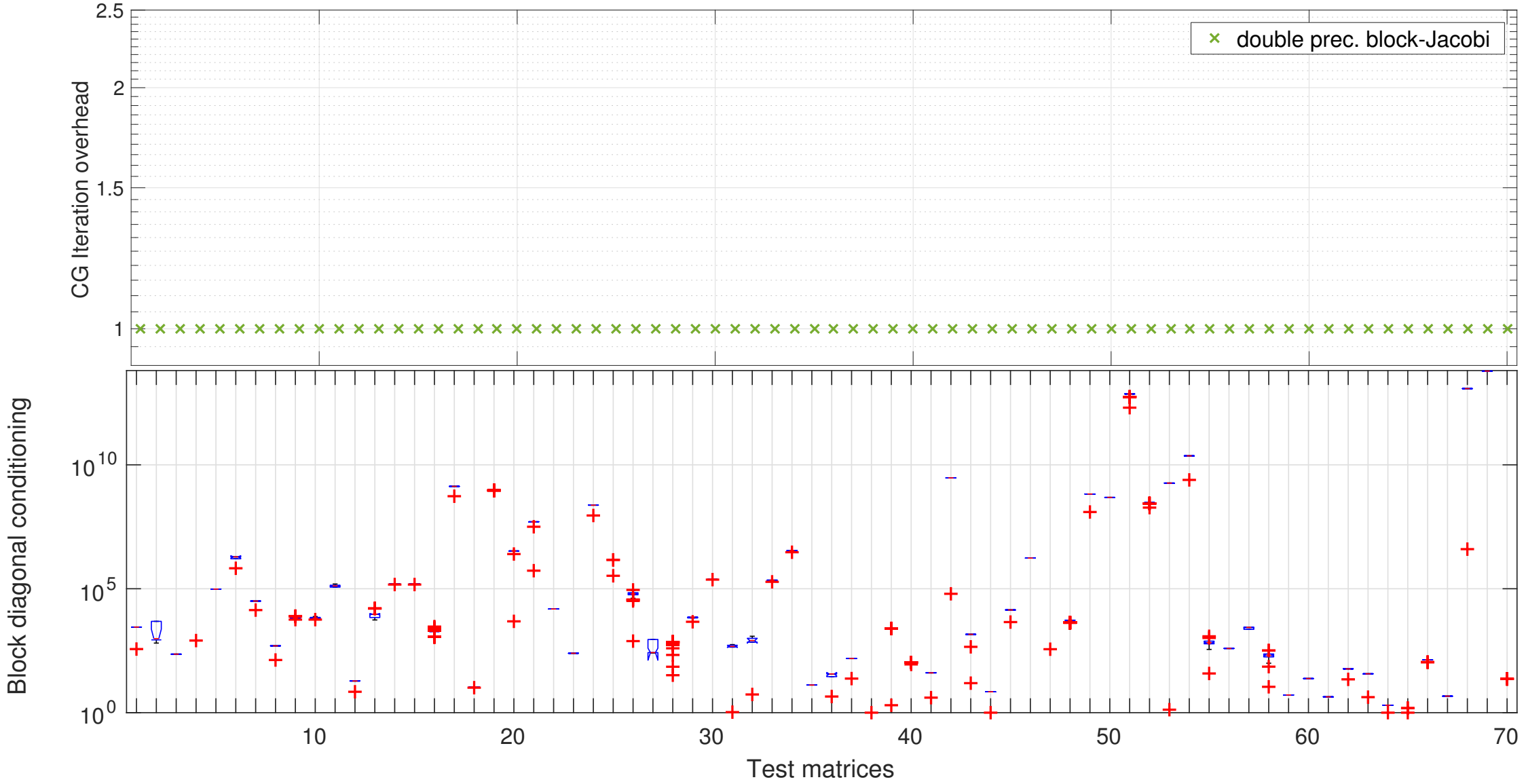

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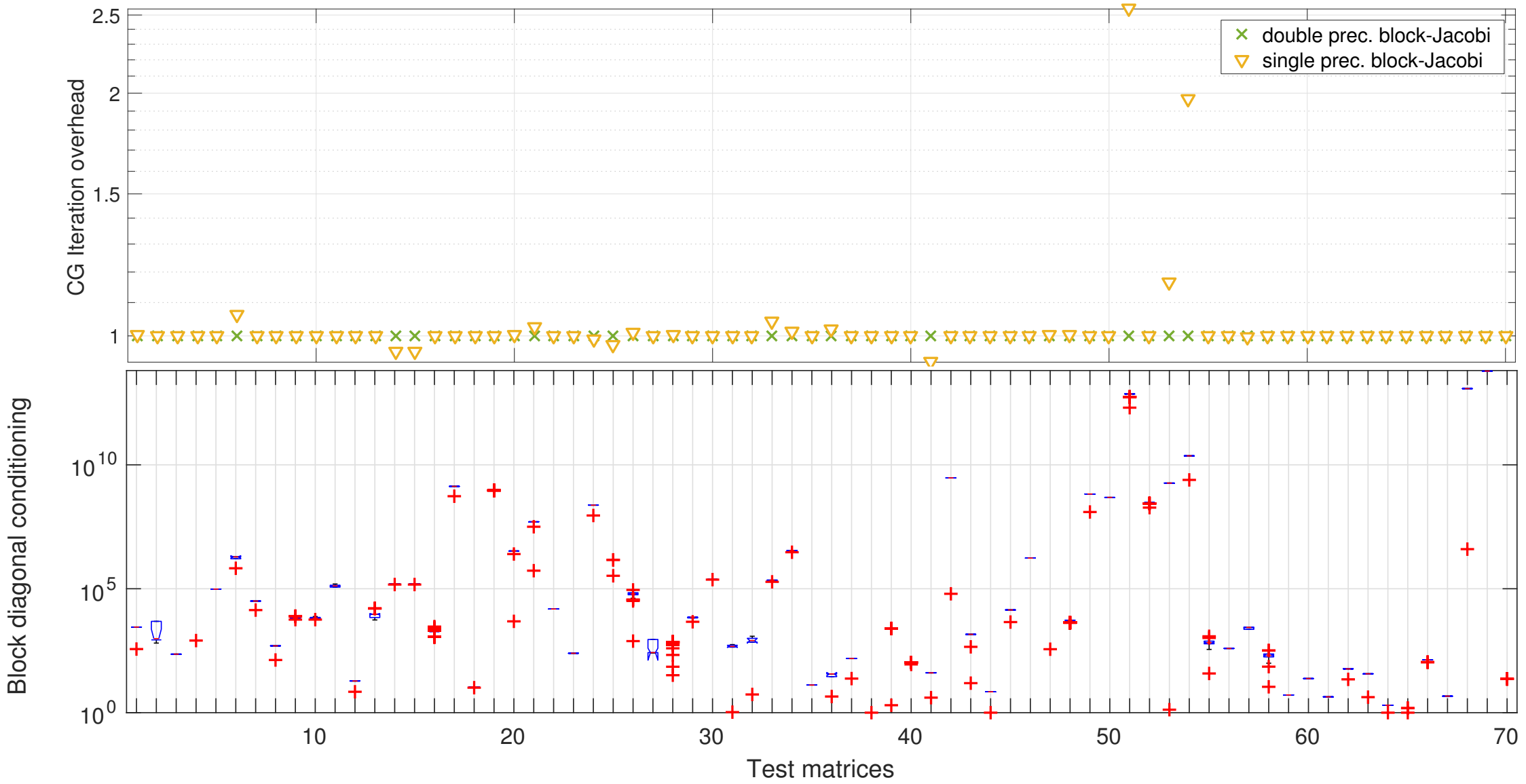

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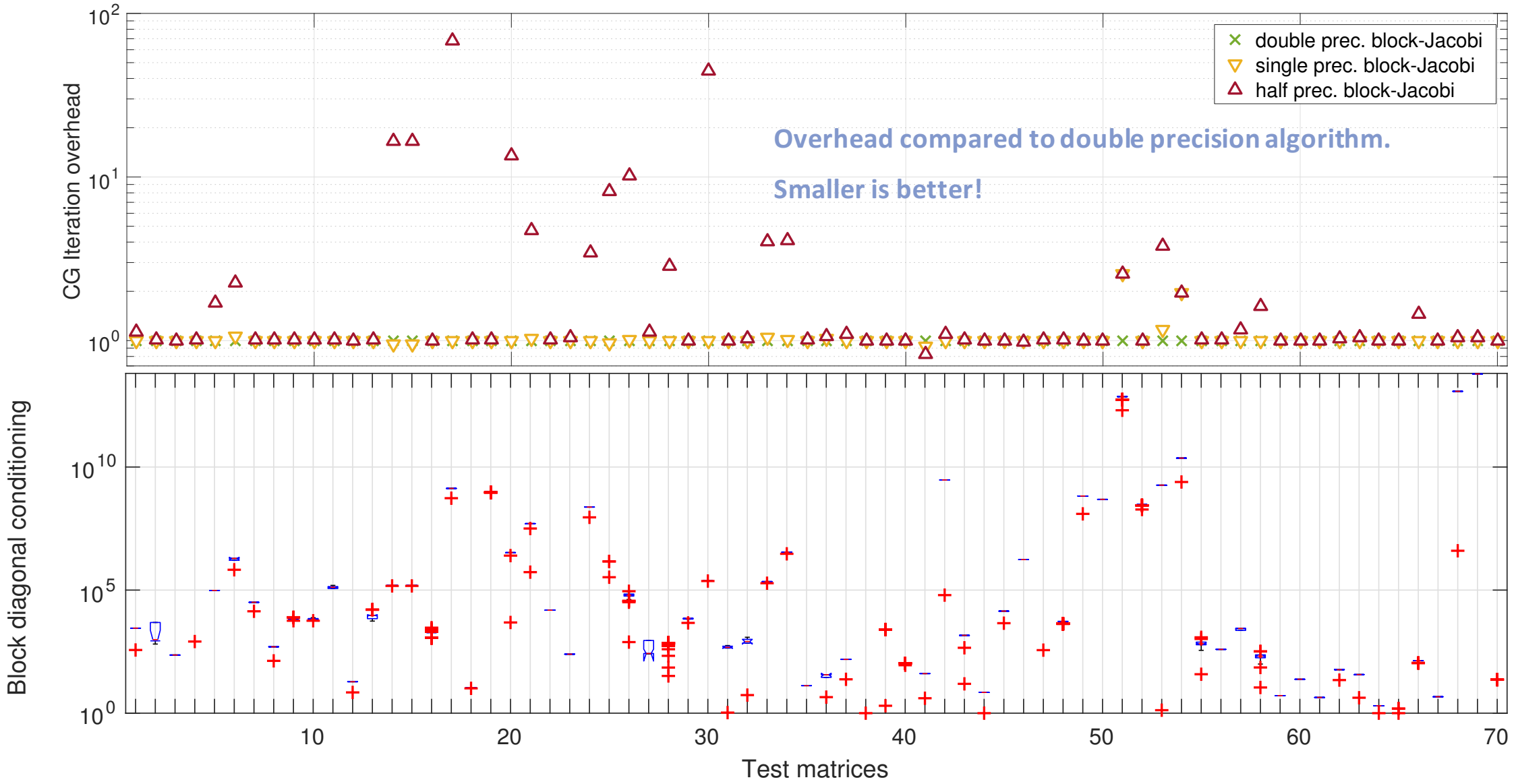
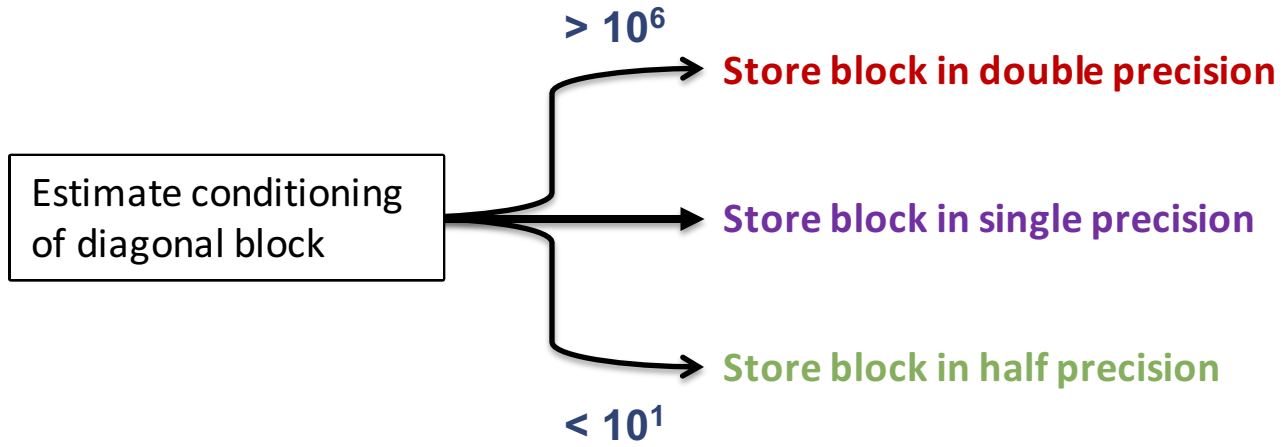


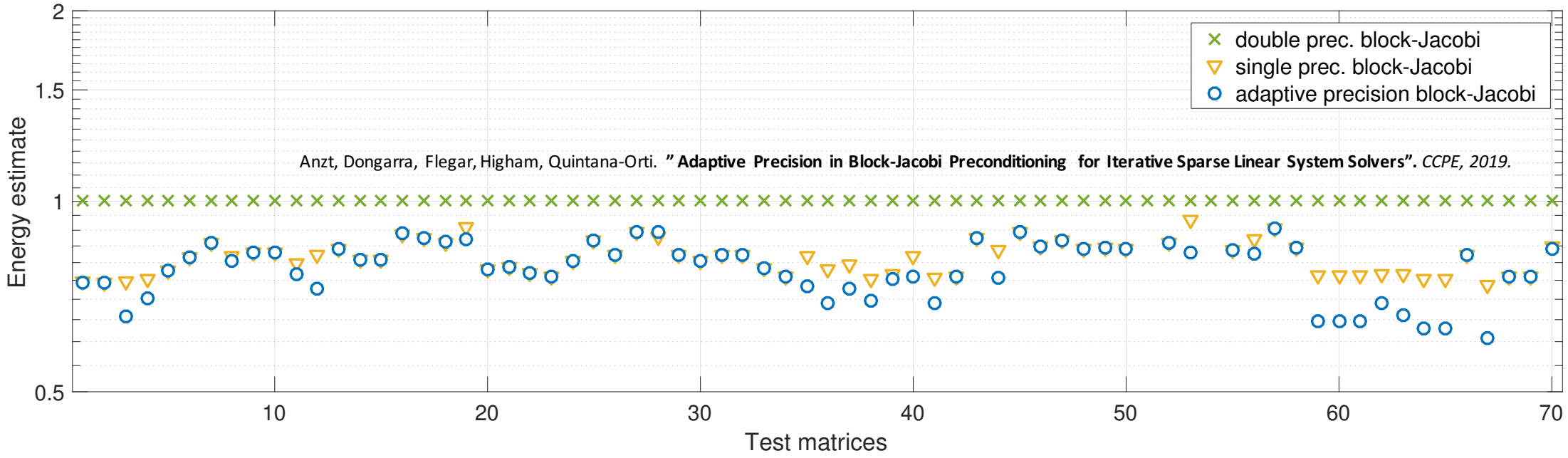
Adaptive Precision Block-Jacobi Preconditioning

Multi-Precision Idea:

- **All computations use double precision!**

- Store distinct blocks in different formats
- Use **single precision as standard** storage format
- Where **necessary:** switch to **double**
- For well-conditioned blocks use **half precision**

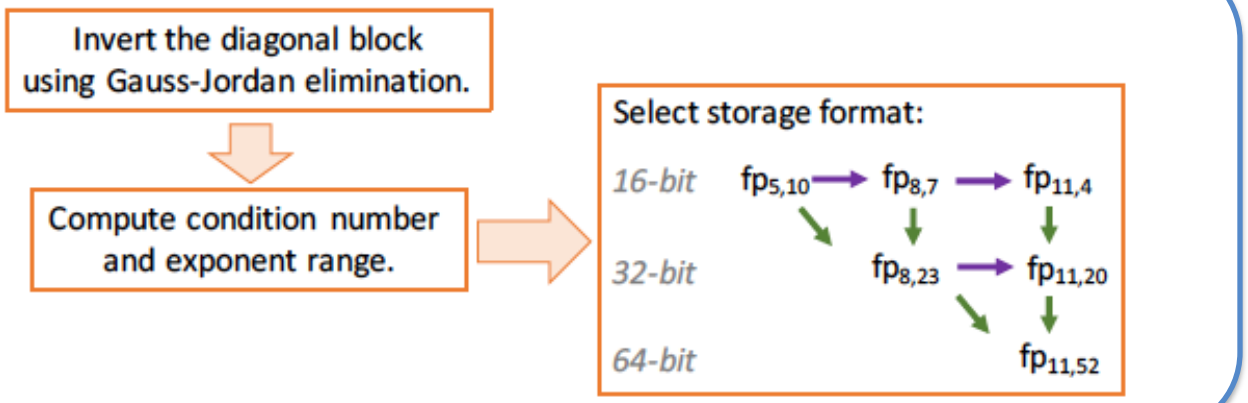




Adaptive Precision Block-Jacobi Preconditioning

Multi-Precision Idea:

- **All computations use double precision!**
- **Depart from the rigid IEEE precision formats!**
- Preserve either 1 or 2 digits accuracy of the inverted diagonal blocks.



Flegar, Anzt, Quintana-Orti. **"Customized-Precision Block-Jacobi Preconditioning for Krylov Iterative Solvers on Data-Parallel Manycore Processors".** *TOMS, submitted.*

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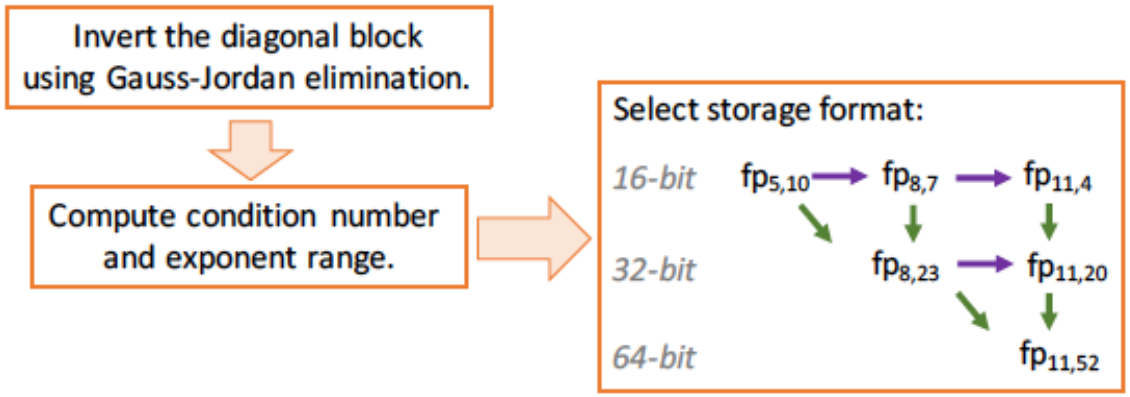

- ✓ Regularity preserved;
- ✓ No flexible Krylov solver needed
  (Preconditioner constant operator);
- ✓ Can handle non-spd problems
  (inversion features pivoting);
- ✓ Preconditioner for any iterative preconditionable solver;

- – Speedups / preconditioner quality **problem-dependent**;
- – **Overhead** of the **precision detection**
  (condition number calculation);
- – **Overhead** from storing **precision information**
  (need to additionally store/retrieve flag);

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Precision distribution in Adaptive Block-Jacobi

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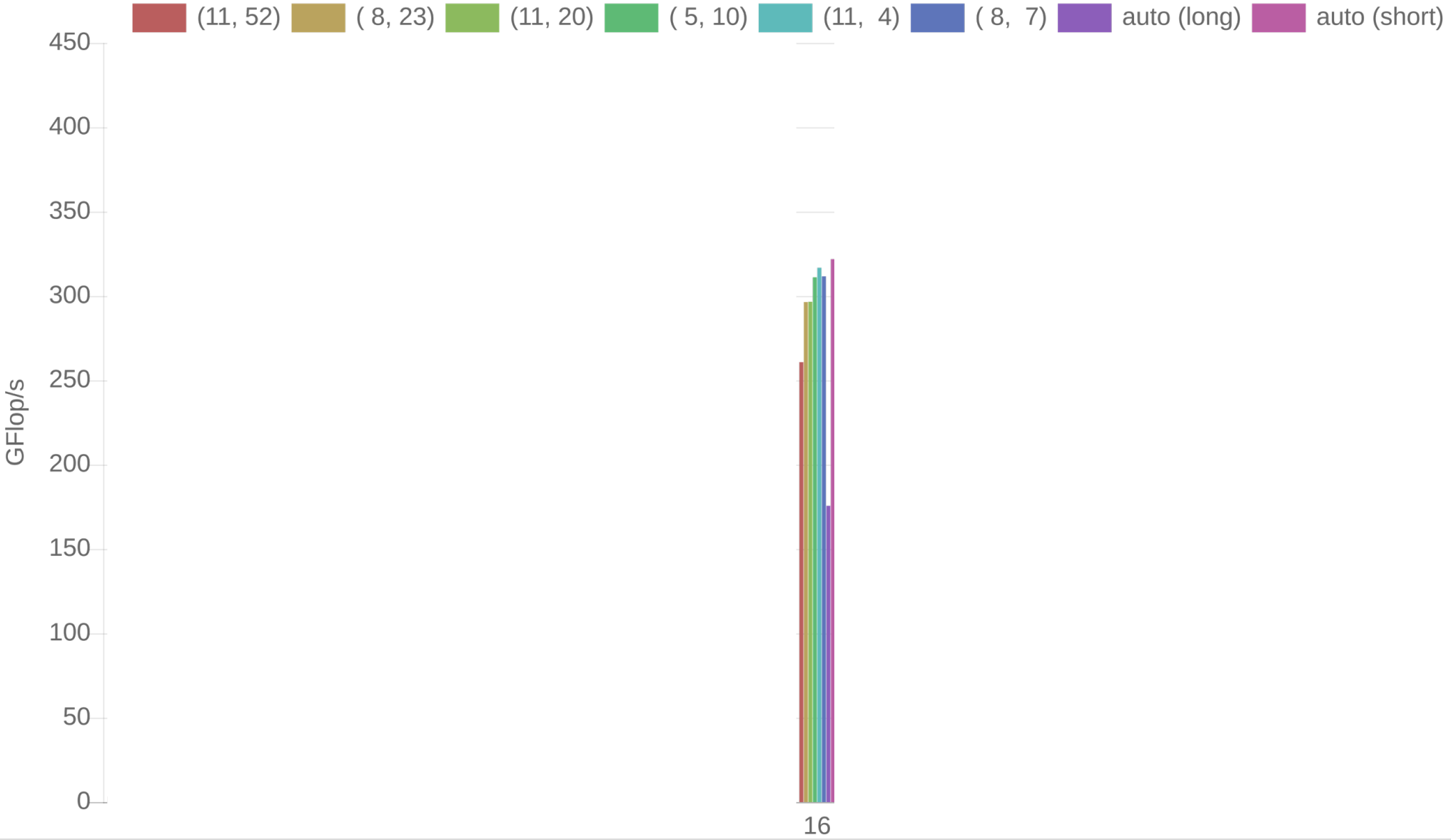
Adaptive Block-Jacobi Generation

NVIDIA V100 GPU



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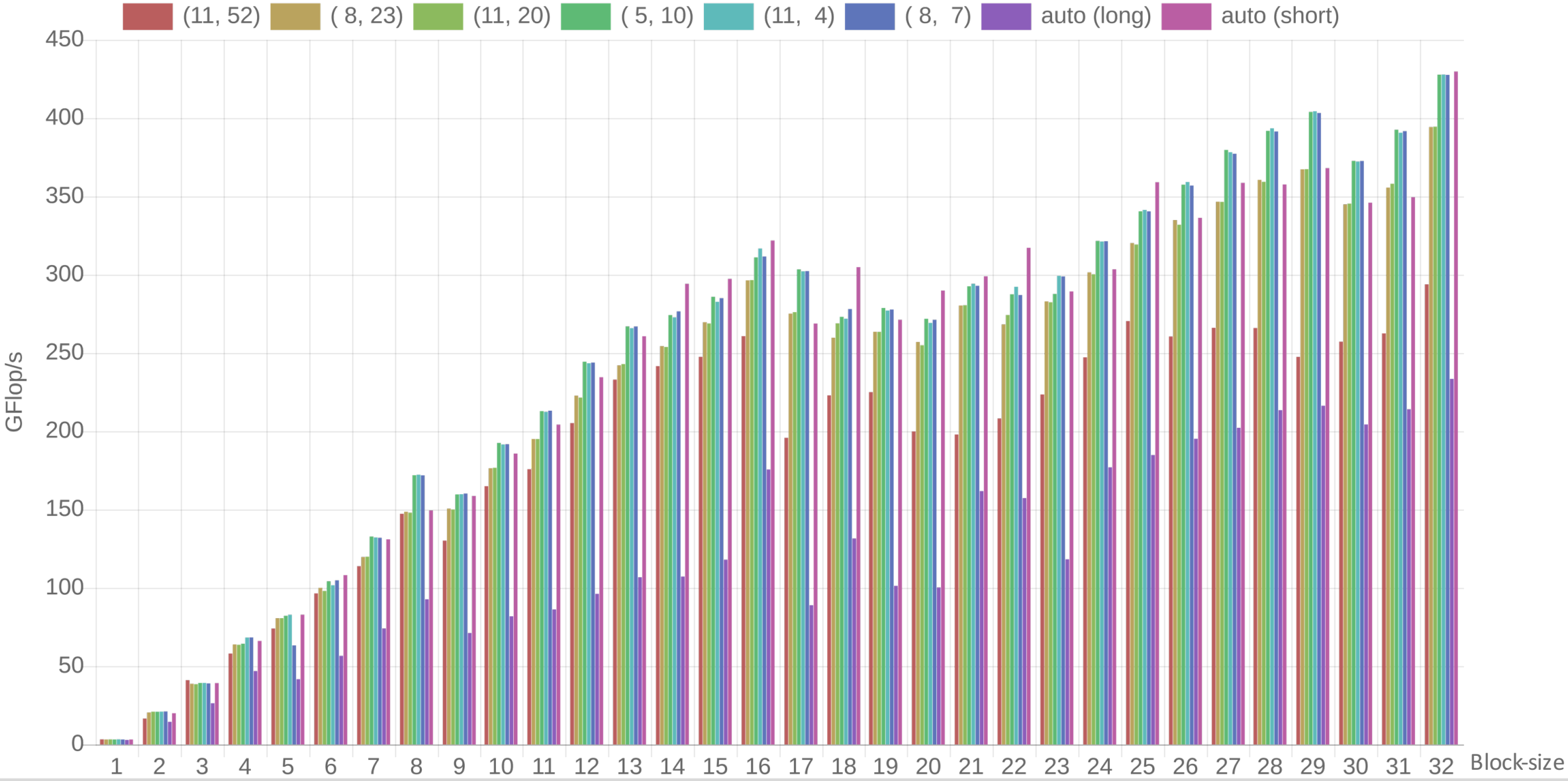

Adaptive Block-Jacobi Application

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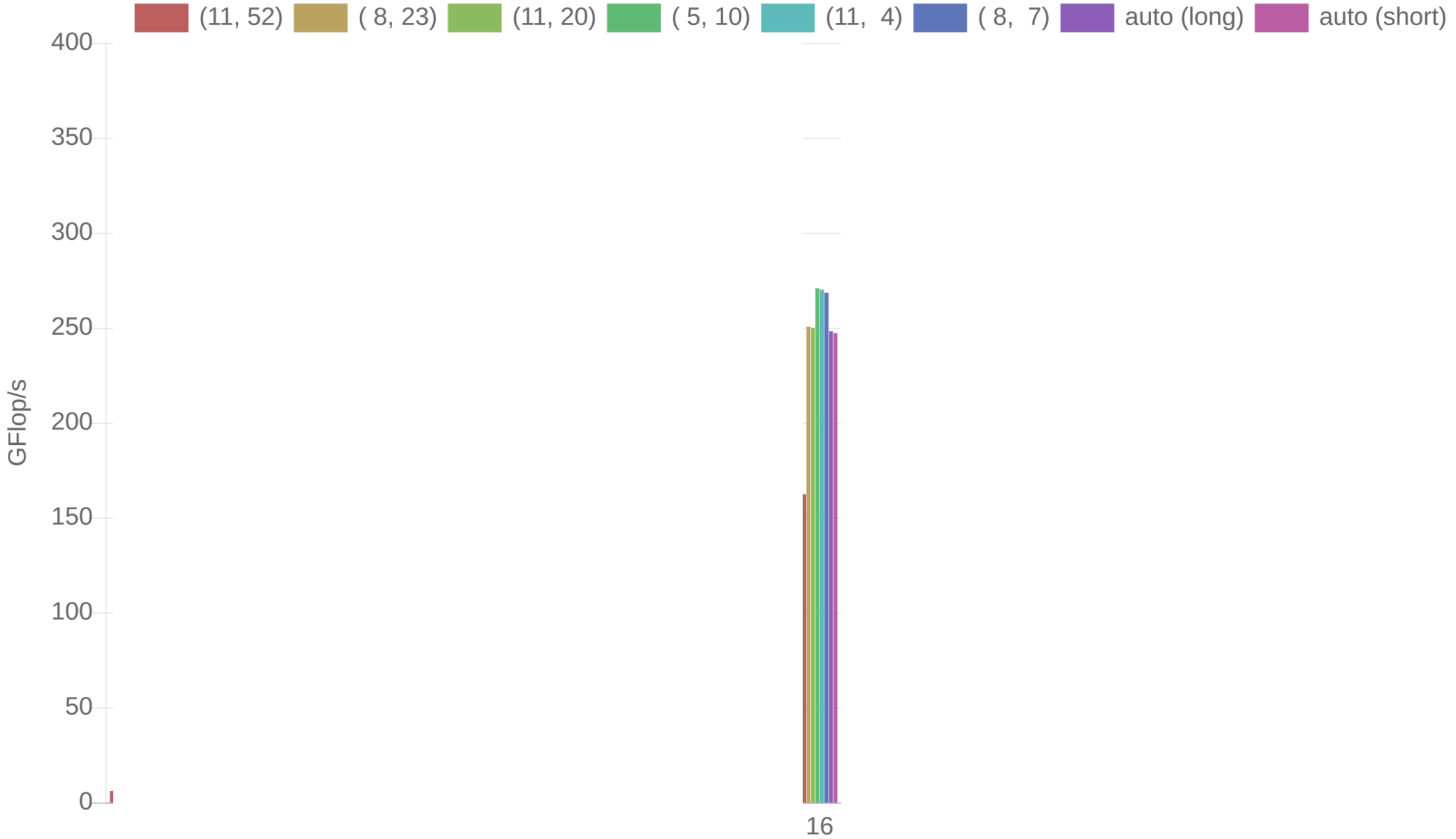

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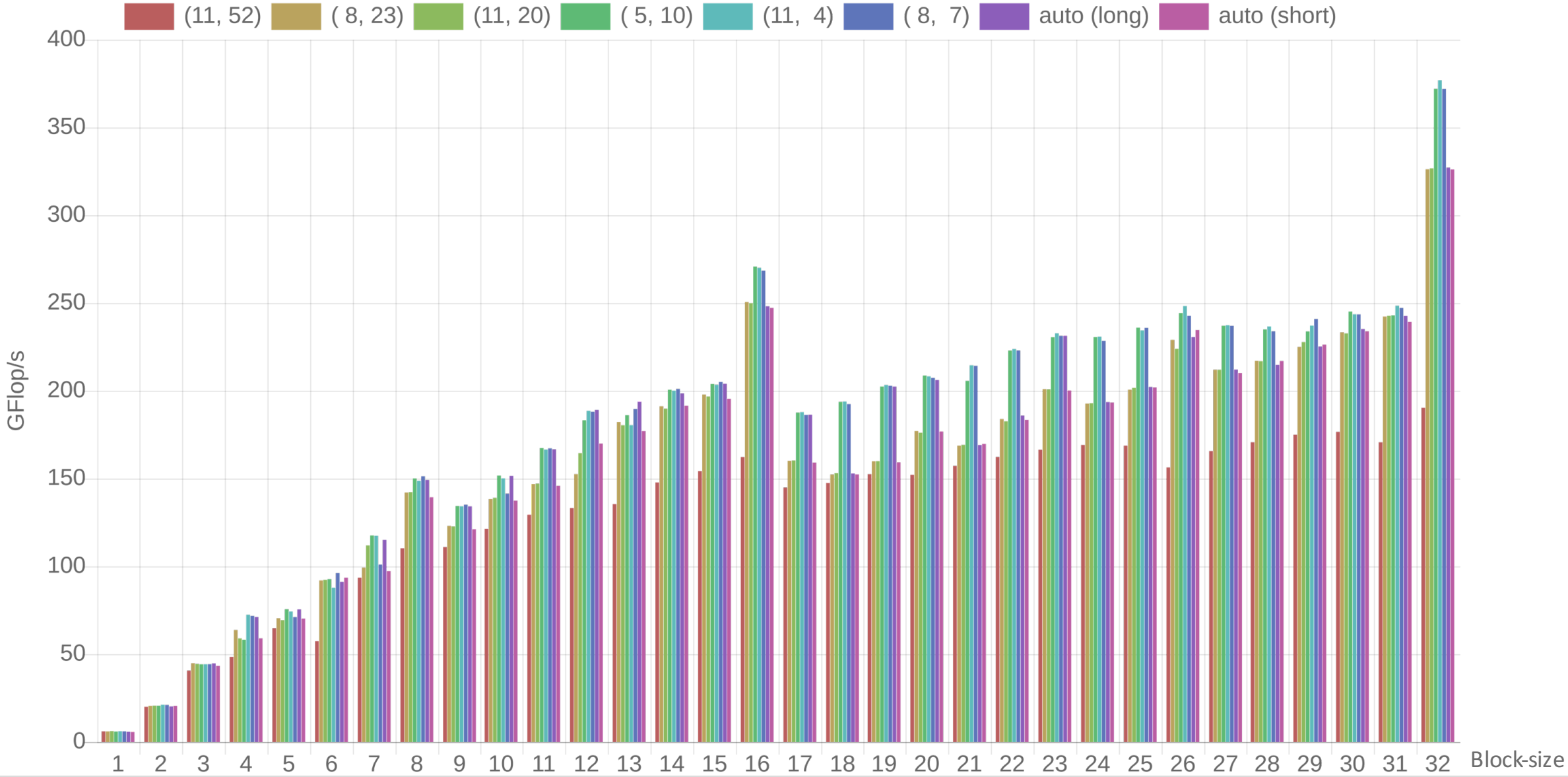
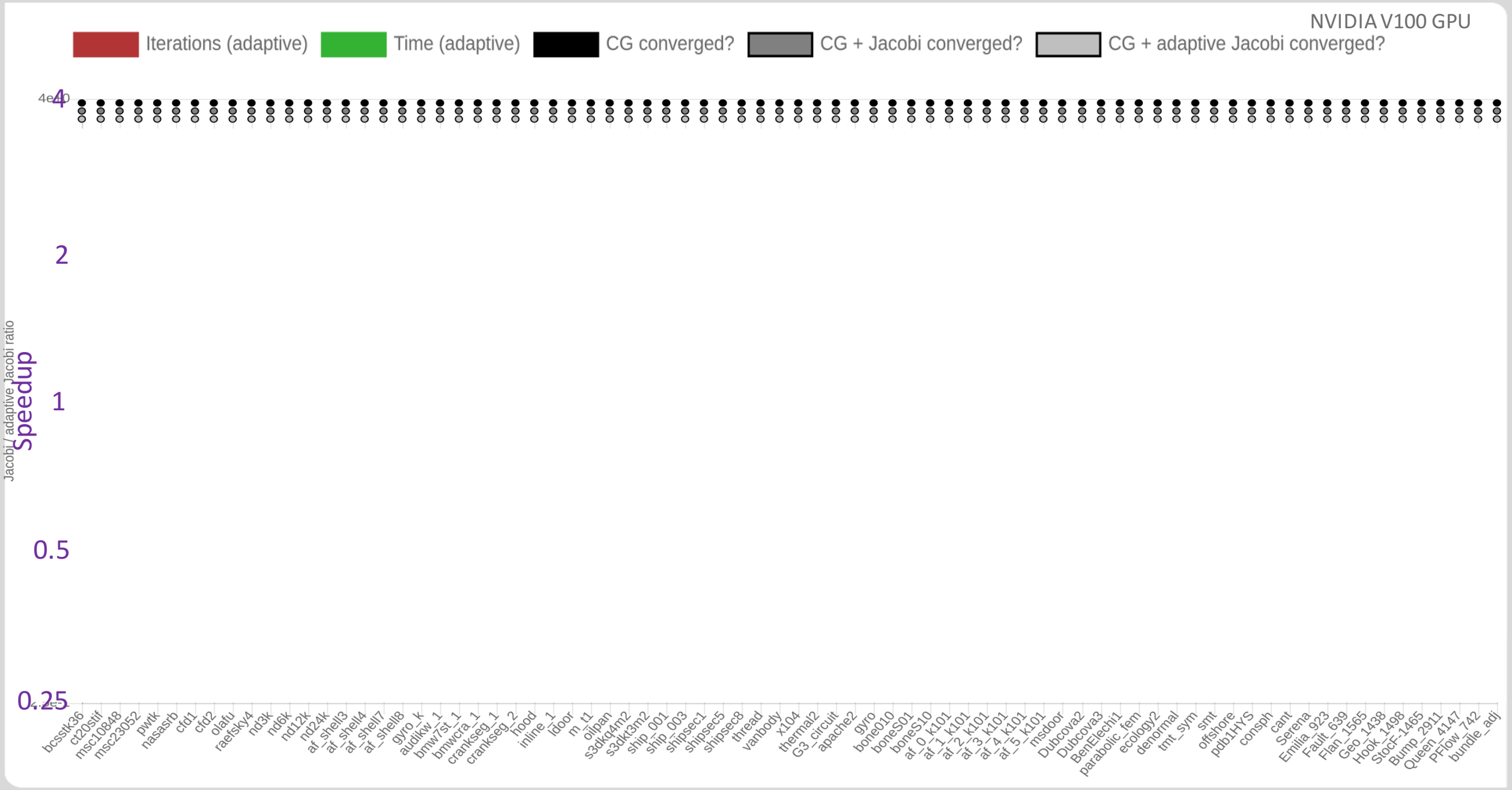
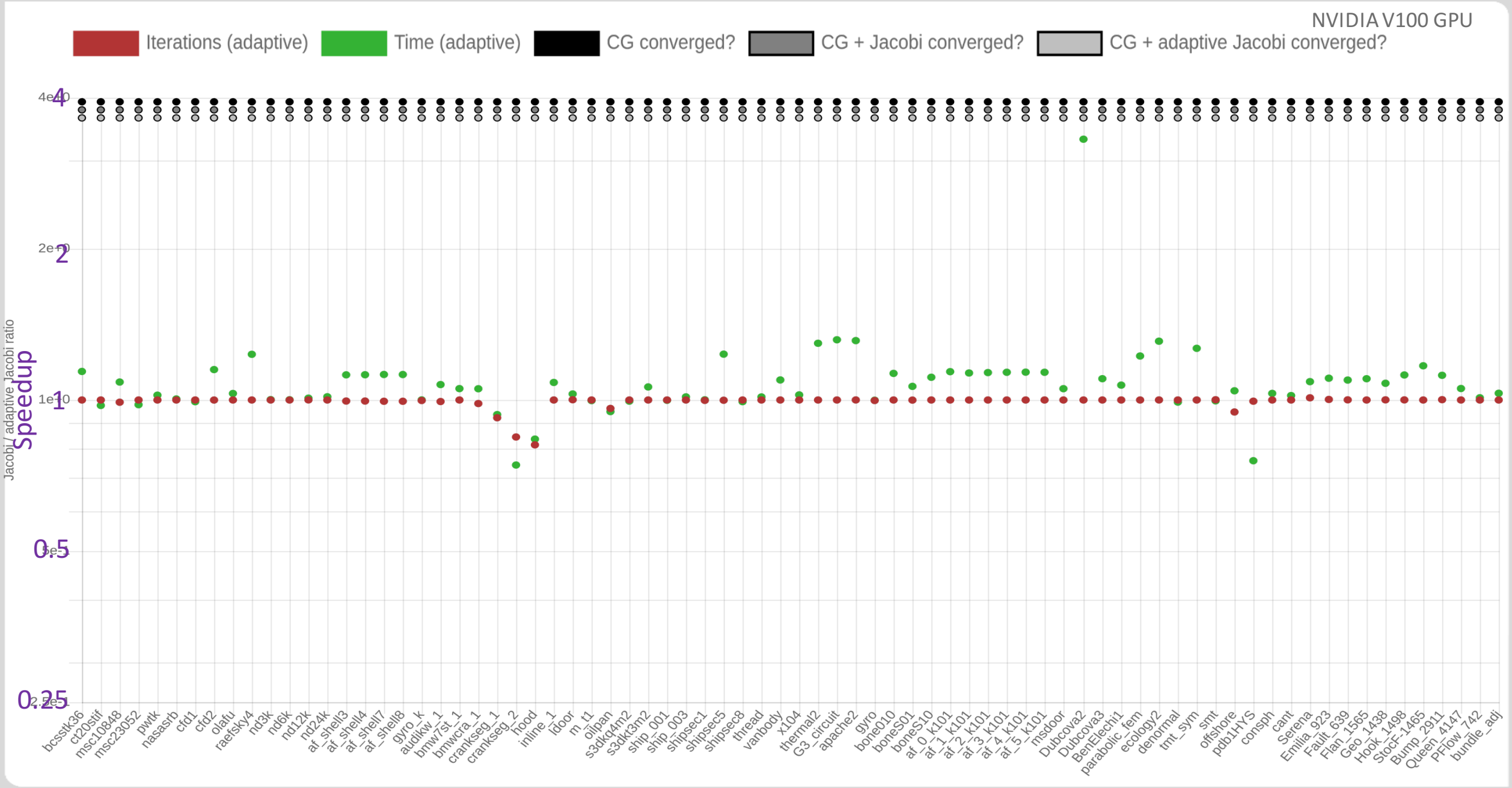



NVIDIA V100 GPU
Iterations (adaptive)
Time (adaptive)
CG converged?
CG + Jacobi converged?
CG + adaptive Jacobi converged?
4e+00
4
2
1
0.5
0.25
Speedup
Jacobi/ adaptive Jacobi ratio
bcsstk36
ct20stif
msc10848
msc23052
pwtk
nasasrb
cfd1
cfd2
olafu
raefsky4
nd3k
nd6k
nd12k
nd24k
af_shell3
af_shell4
af_shell7
af_shell8
gyro_k
audikw_1
bmw7st_1
bmwcra_1
crankseg_1
crankseg_2
hood
inline_1
ldoor
m_t1
oilpan
s3dkq4m2
s3dkt3m2
ship_001
ship_003
shipsec1
shipsec5
shipsec8
thread
vanbody
x104
thermal2
G3_circuit
apache2
gyro
boneS10
boneS01
af_0_k101
af_1_k101
af_2_k101
af_3_k101
af_4_k101
af_5_k101
msdoor
Dubcova2
Dubcova3
BenElechi1
parabolic_fem
ecology2
denormal
tmt_sym
smt
offshore
pdb1HYS
consph
cant
Serena
Emilia_923
Fault_639
Flan_1565
Geo_1438
Hook_1498
StocF-1465
Bump_2911
Queen_4147
PFlow_742
bundle_adj
Problem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nasasrb
cfd1
cfd2
olafu
raefsky4
nd3k
nd6k
nd12k
nd24k
af_shell3
af_shell4
af_shell7
af_shell8
gyro_k
audikw_1
bmw7st_1
bmwcra_1
crankseg_1
crankseg_2
hood
inline_1
ldoor
m_t1
oilpan
s3dkq4m2
s3dkt3m2
ship_001
ship_003
shipsec1
shipsec5
shipsec8
thread
vanbody
x104
thermal2
G3_circuit
apache2
gyro
boneS01
boneS10
af_0_k101
af_1_k101
af_2_k101
af_3_k101
af_4_k101
af_5_k101
msdoor
Dubcova2
Dubcova3
BenElechi1
parabolic_fem
ecology2
denormal
tmt_sym
smt
offshore
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consph
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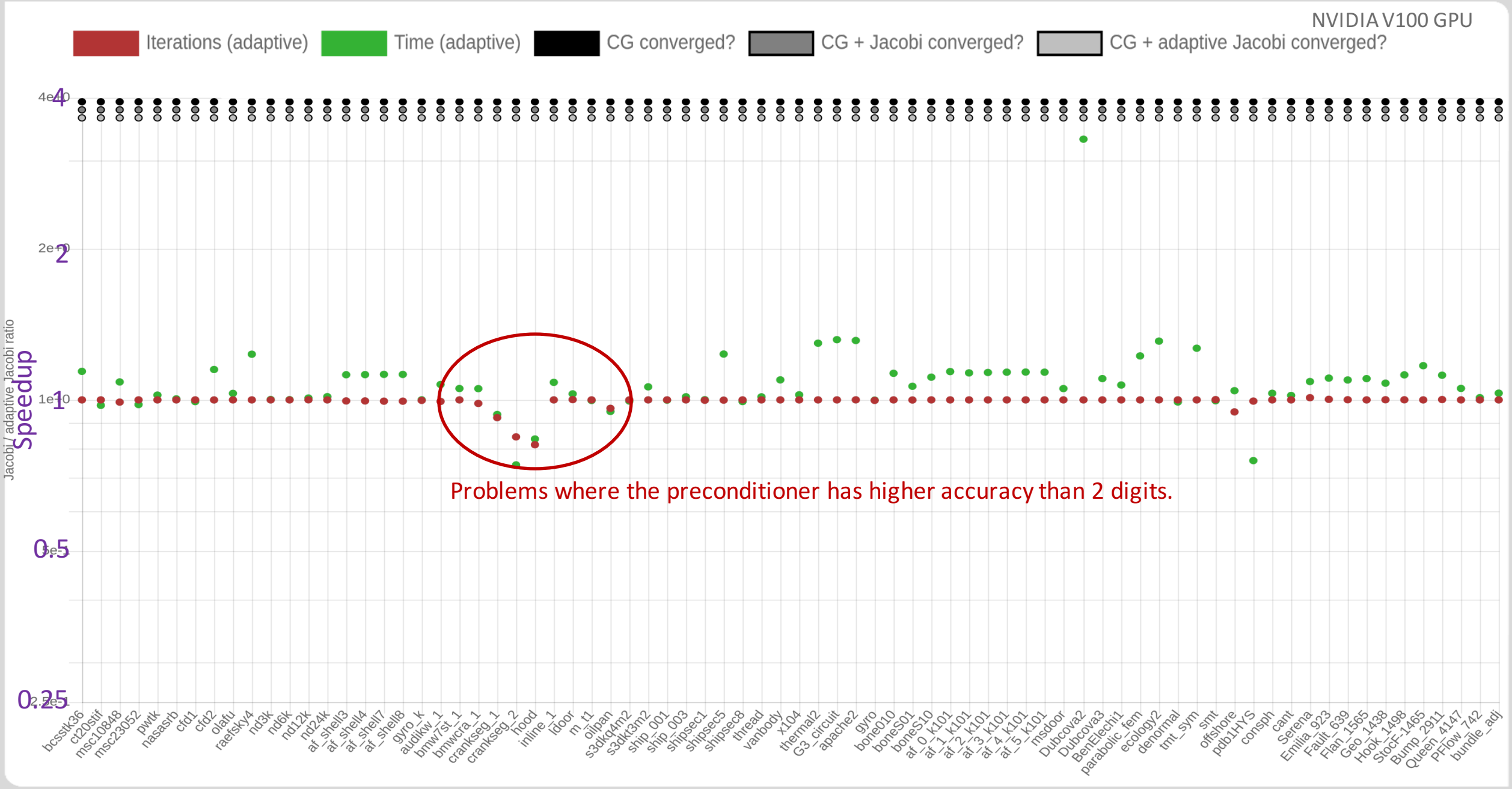
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Problems where the preconditioner has higher accuracy than 2 digits.
Problem
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nasasrb
cfd1
cfd2
olafu
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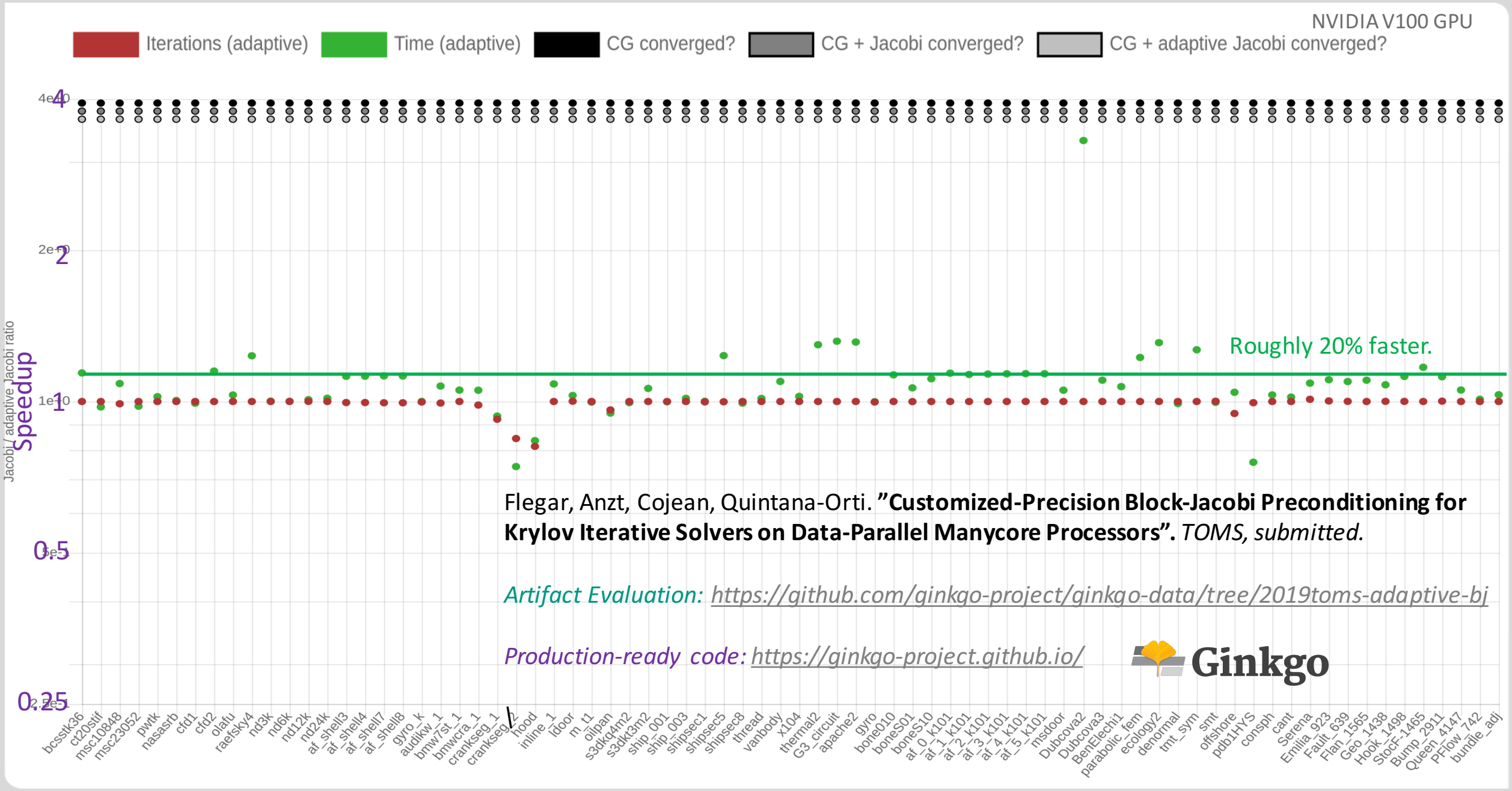
nd3k
nd6k
nd12k
nd24k
af_shell3
af_shell4
af_shell7
af_shell8
gyro_k
audikw_1
bmw7st_1
bmwcra_1
crankseg_1
crankseg_2
hood
inline_1
ldoor
m_t1
oilpan
s3dkq4m2
s3dkt3m2
ship_001
ship_003
shipsec1
shipsec5
shipsec8
thread
vanbody
x104
thermal2
G3_circuit
apache2
gyro
boneS01
boneS10
af_0_k101
af_1_k101
af_2_k101
af_3_k101
af_4_k101
af_5_k101
msdoor
Dubcova2
Dubcova3
BenElechi1
parabolic_fem
ecology2
denormal
tmt_sym
smt
offshore
pdb1HYS
consph
cant
Serena
Emilia_923
Fault_639
Flan_1565
Geo_1438
Hook_1498
StocF-1465
Bump_2911
Queen_4147
PFlow_742
bundle_adj


NVIDIA V100 GPU
Iterations (adaptive)
Time (adaptive)
CG converged?
CG + Jacobi converged?
CG + adaptive Jacobi converged?
Speedup
Jacobi/ adaptive Jacobi ratio
4
2
1
0.5
0.25
Roughly 20% faster.
Flegar, Anzt, Cojean, Quintana-Orti. **"Customized-Precision Block-Jacobi Preconditioning for Krylov Iterative Solvers on Data-Parallel Manycore Processors".** *TOMS, submitted.*
Artifact Evaluation: https://github.com/ginkgo-project/ginkgo-data/tree/2019toms-adaptive-bj
Production-ready code: https://ginkgo-project.github.io/
Ginkgo
bcsstk36
ct20stif
msc10848
msc23052
pwtk
nasasrb
cfd1
cfd2
olafu
raefsky4
nd3k
nd6k
nd12k
nd24k
af_shell3
af_shell4
af_shell7
af_shell8
gyro_k
audikw_1
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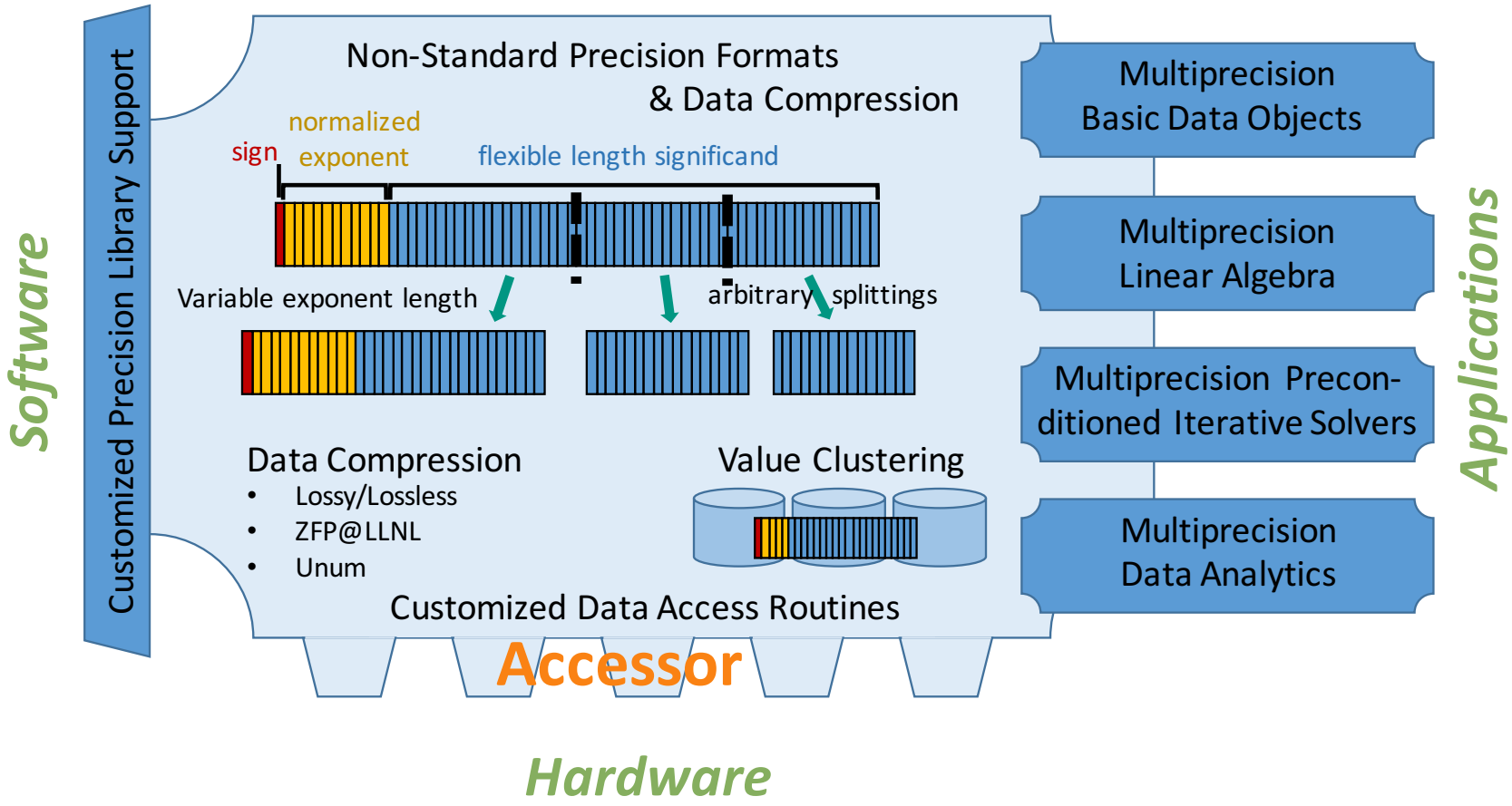
Problem

Towards a Modular Precision Ecosystem

- Creating a **Modular Precision Ecosystem** inside Ginkgo .



Core Concept: Separate Algorithm from Kernels

Ginkgo

Library core contains architecture-agnostic algorithm implementation;

Core

Library Infrastructure
Algorithm Implementations
- Iterative Solvers
- Preconditioners
- …

Architecture-specific kernels execute the algorithm on target architecture;

Kernels

- Accessor
- SpMV
- Solver kernels
- Precond kernels
- …

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Reference are sequential kernels to check correctness of algorithm design and optimized kernels;

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Ginkgo

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Runtime polymorphism selects the right kernel depending on the target architecture;

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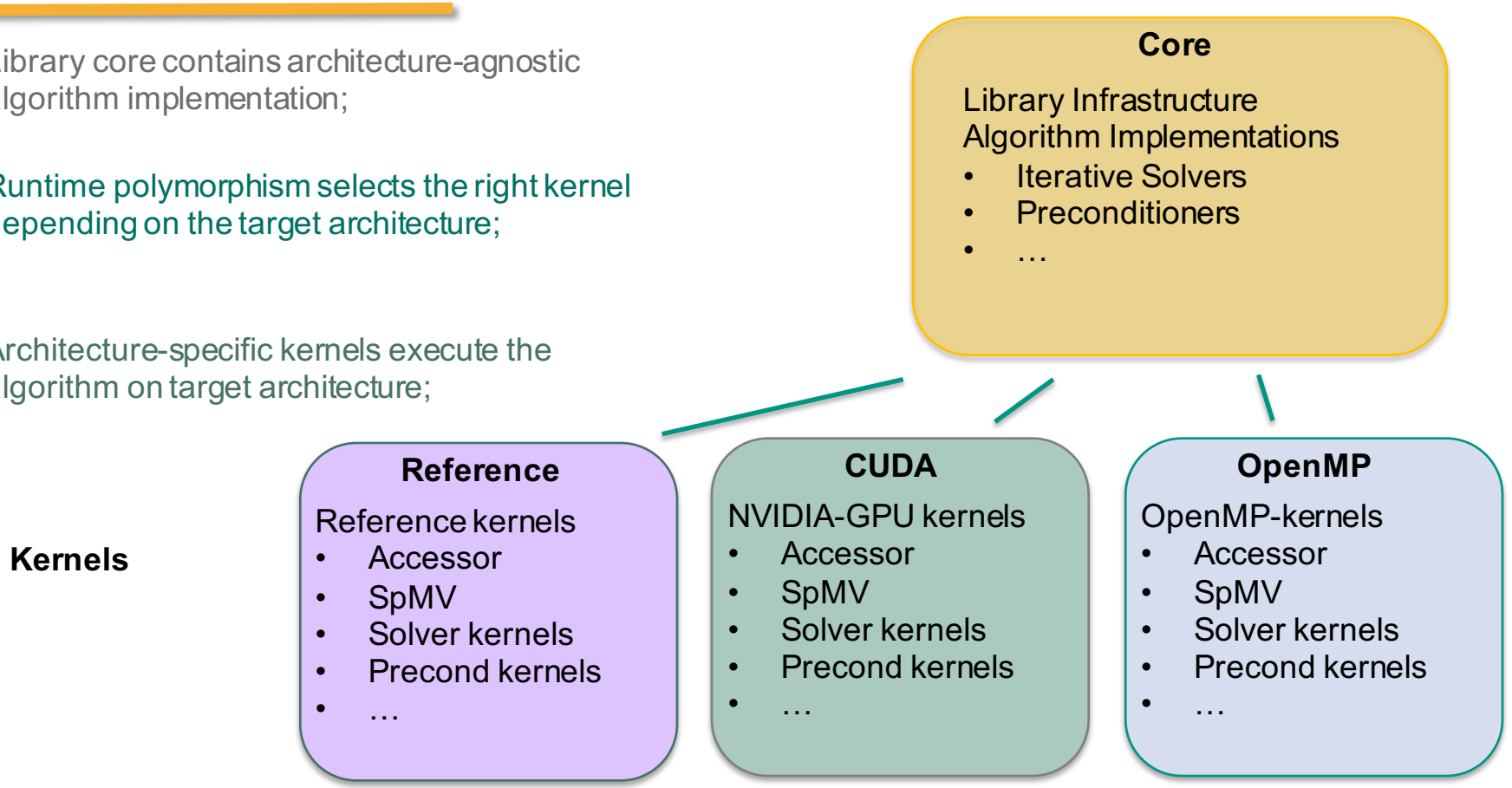

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CUDA

NVIDIA-GPU kernels
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- SpMV
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- …

OpenMP

OpenMP-kernels
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- …

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OpenMP-kernels
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- SpMV
- Solver kernels
- Precond kernels
- …

HIP

AMD-GPU kernels
- Accessor
- SpMV

Multi-GPU

NVIDIA-GPU kernels
- Accessor
- SpMV
- Solver kernels
- Precond kernels
- …

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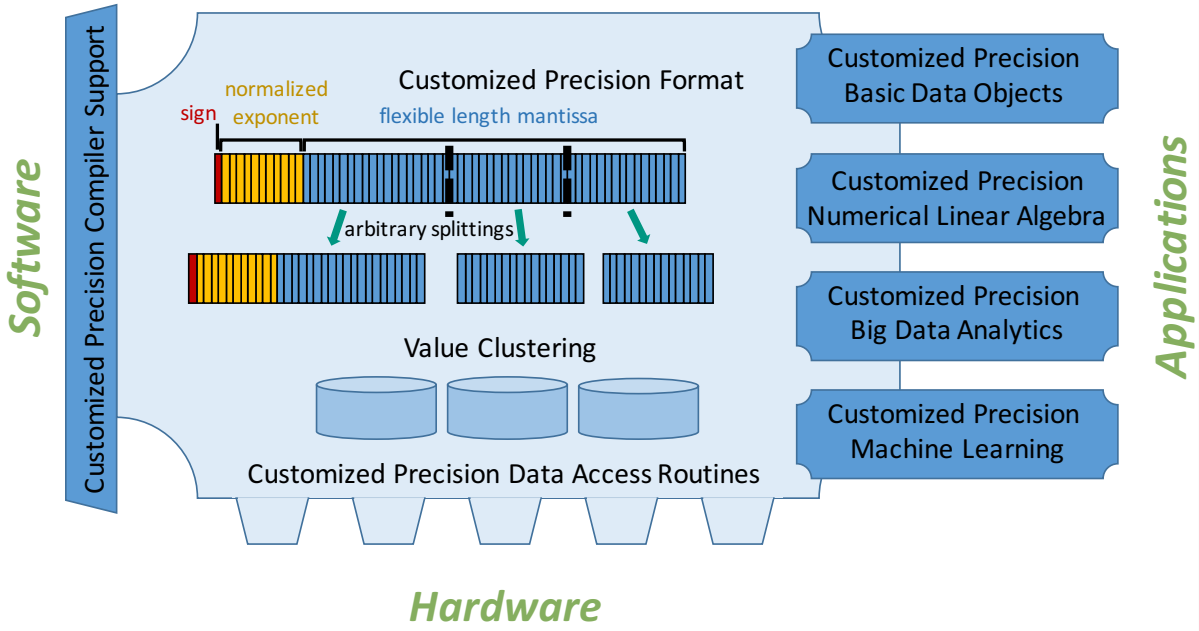
Optimized architecture-specific kernels;

Summary and next steps

- **Decouple arithmetic precision from memory precision.**
- Using **customized precisions** for memory operations.
- Speedup of up to 1.3x for adaptive precision block-Jacobi preconditioning.
- Creating a **Modular Precision Ecosystem** inside Ginkgo.
  https://github.com/ginkgo-project/ginkgo



EXASCALE COMPUTING PROJECT

HELMHOLTZ
RESEARCH FOR GRAND CHALLENGES

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