14th International Workshop on OpenCL and SYCL

IWOCL 2026

Comparing the Performance of Heterogeneous Conjugate Gradient and Cholesky Solvers on Various Hardware Using SYCL

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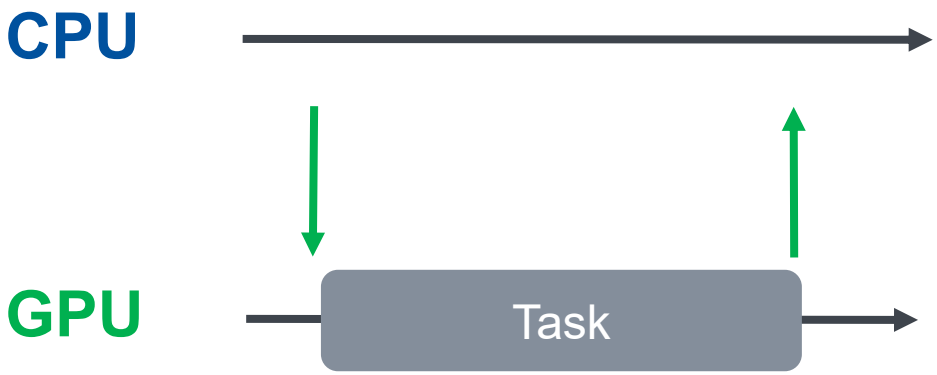
Tim Thüring, Alexander Strack, and Dirk Pflüger, University of Stuttgart.

May 6-8, 2026 | Heilbronn, Germany | iwocl.org

Motivation
Heterogeneous computing

Classic approach



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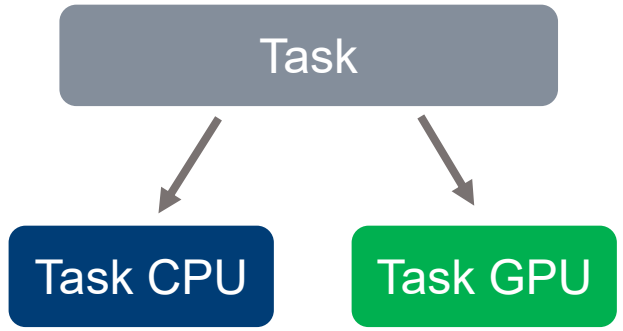

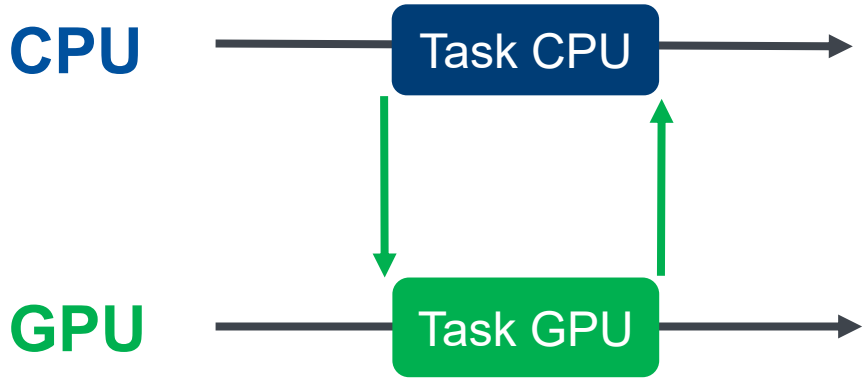

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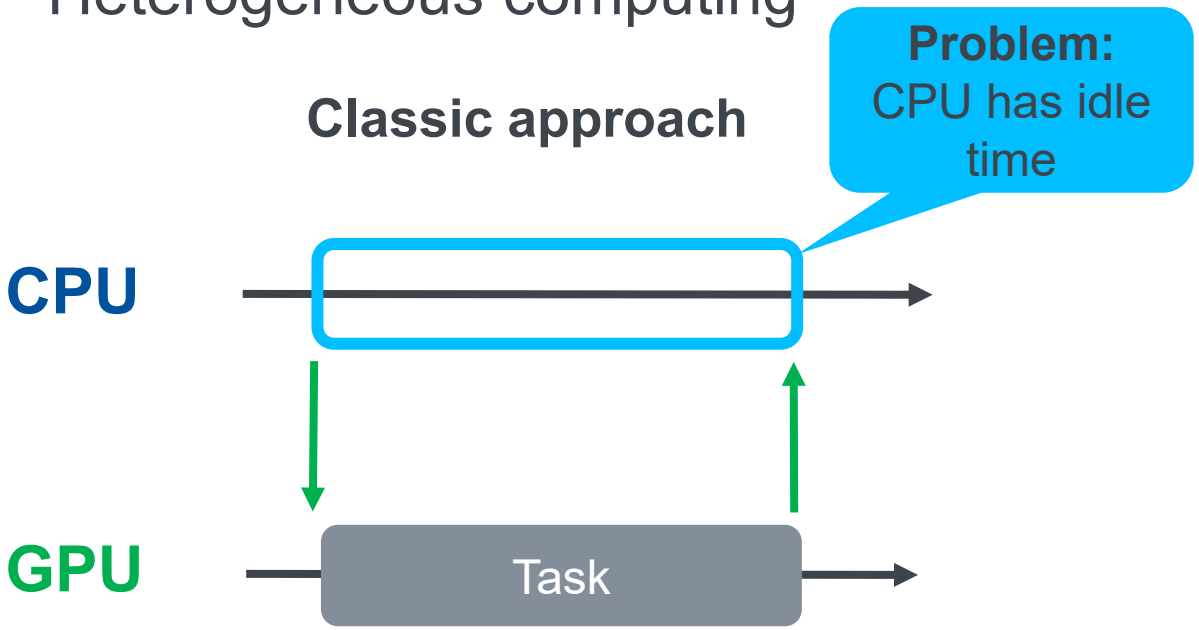

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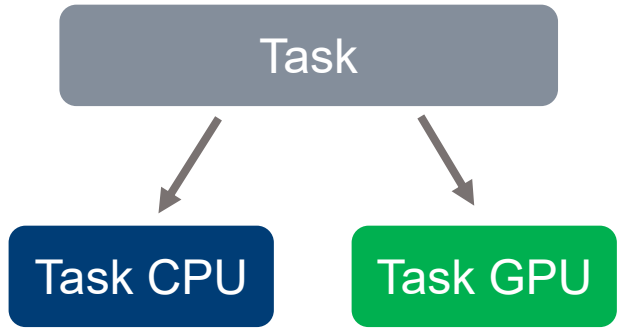

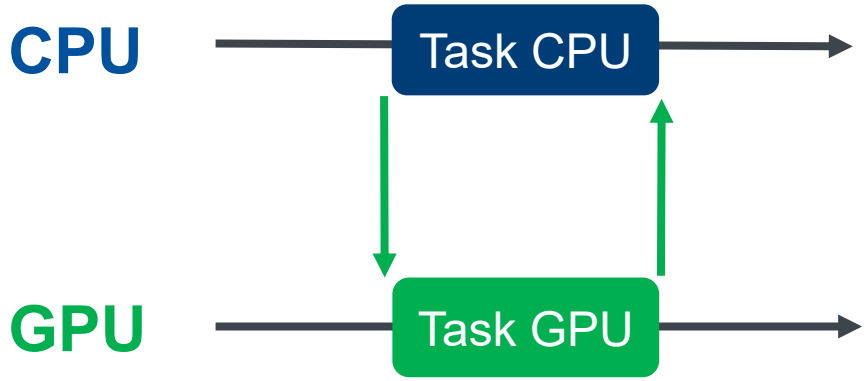

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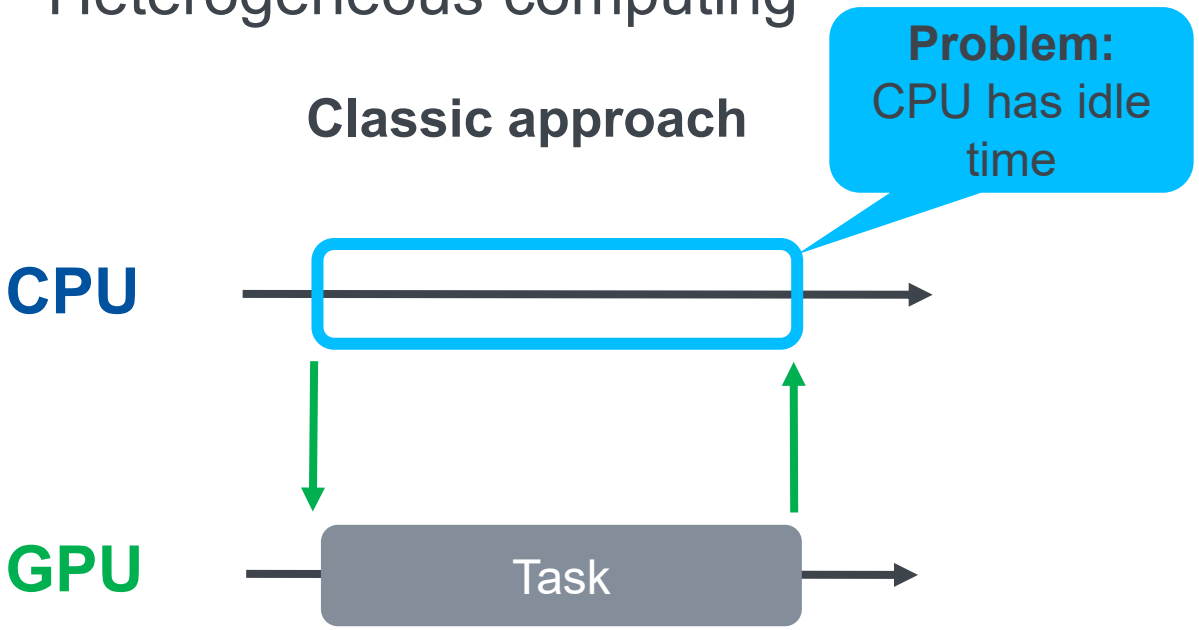

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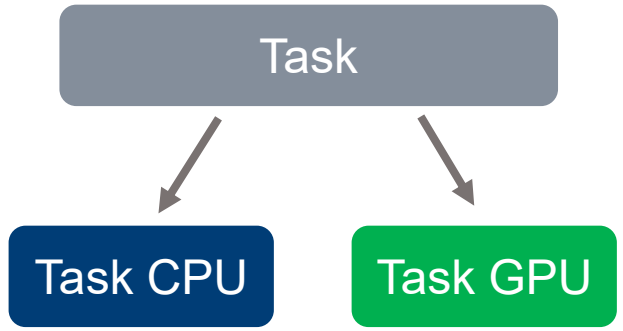

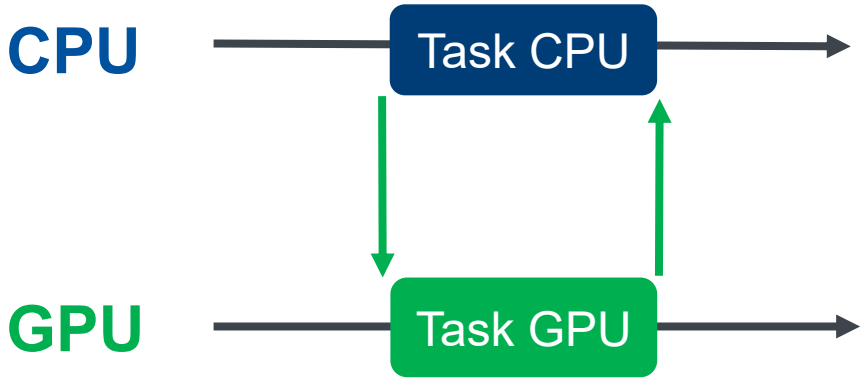

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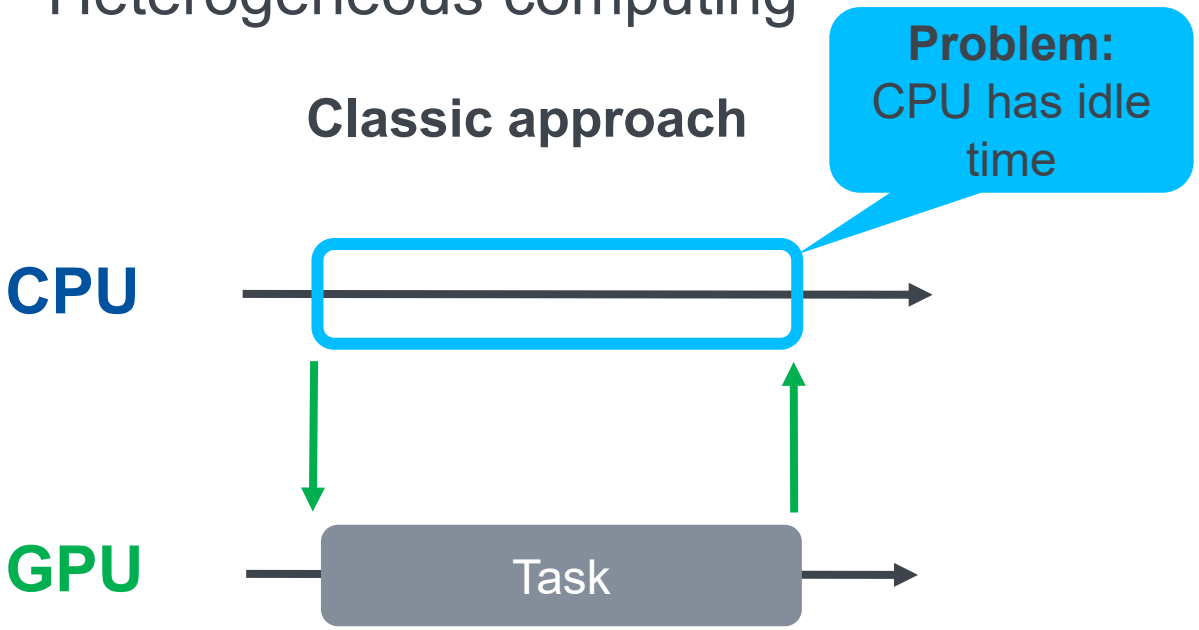

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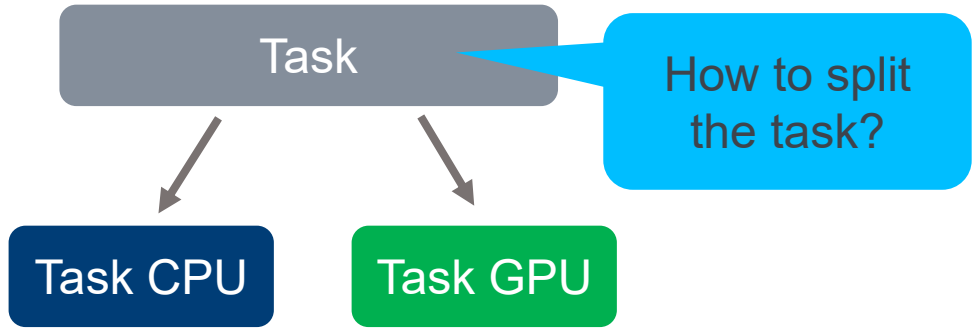

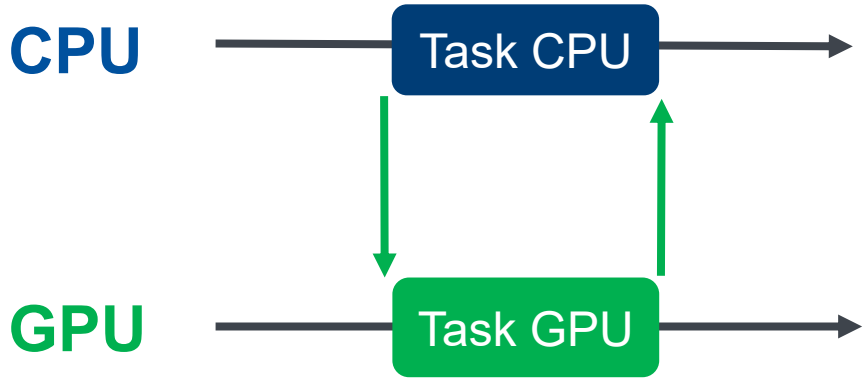

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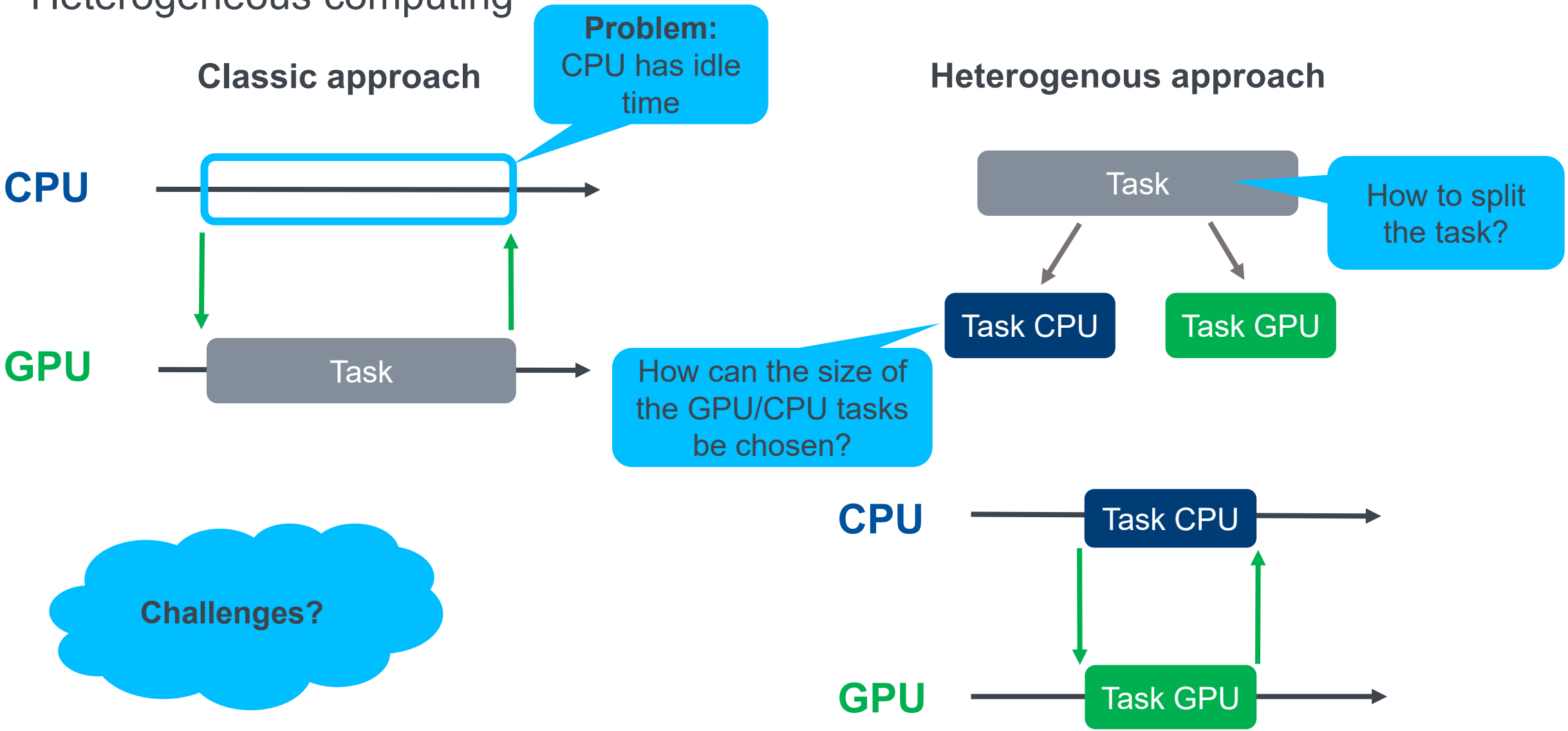

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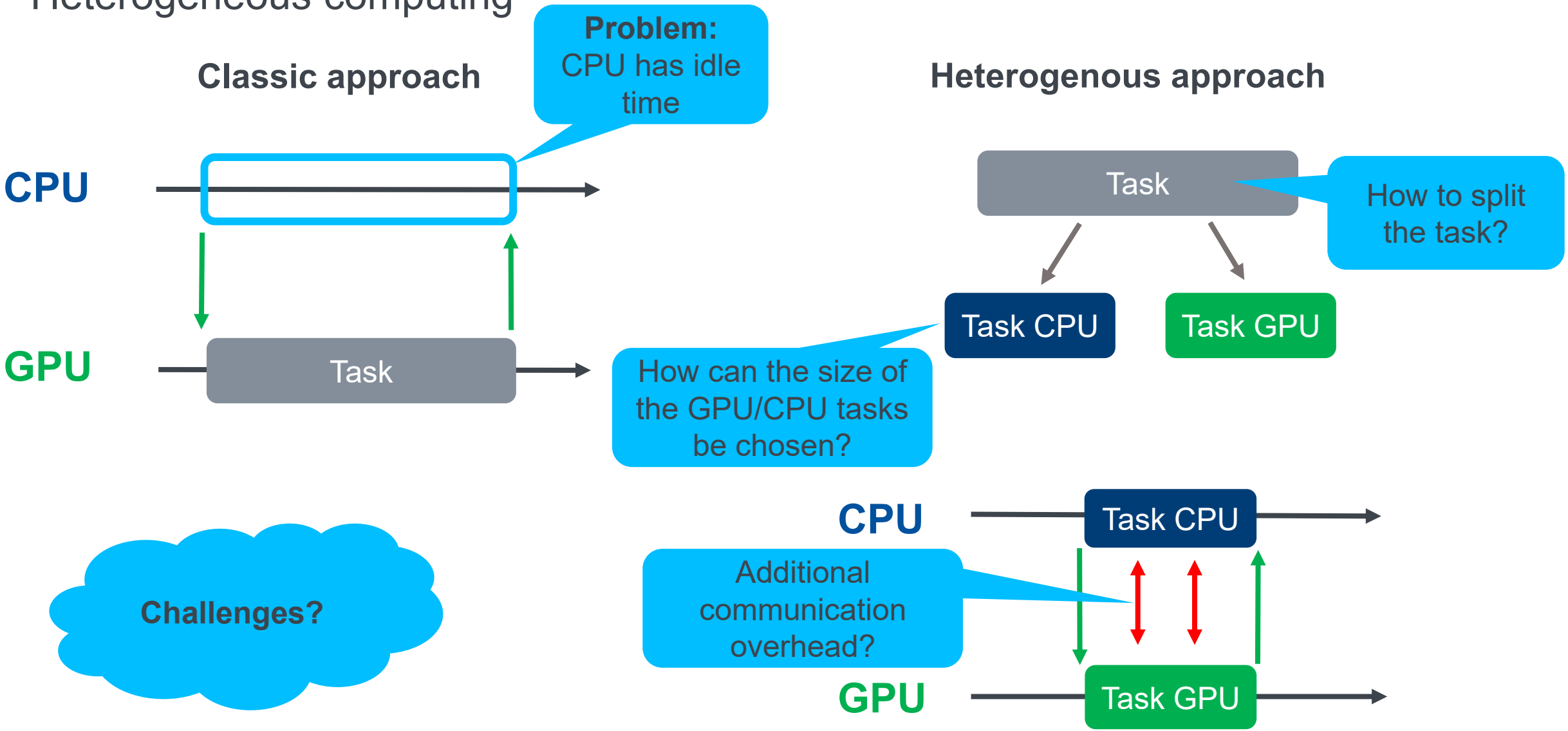

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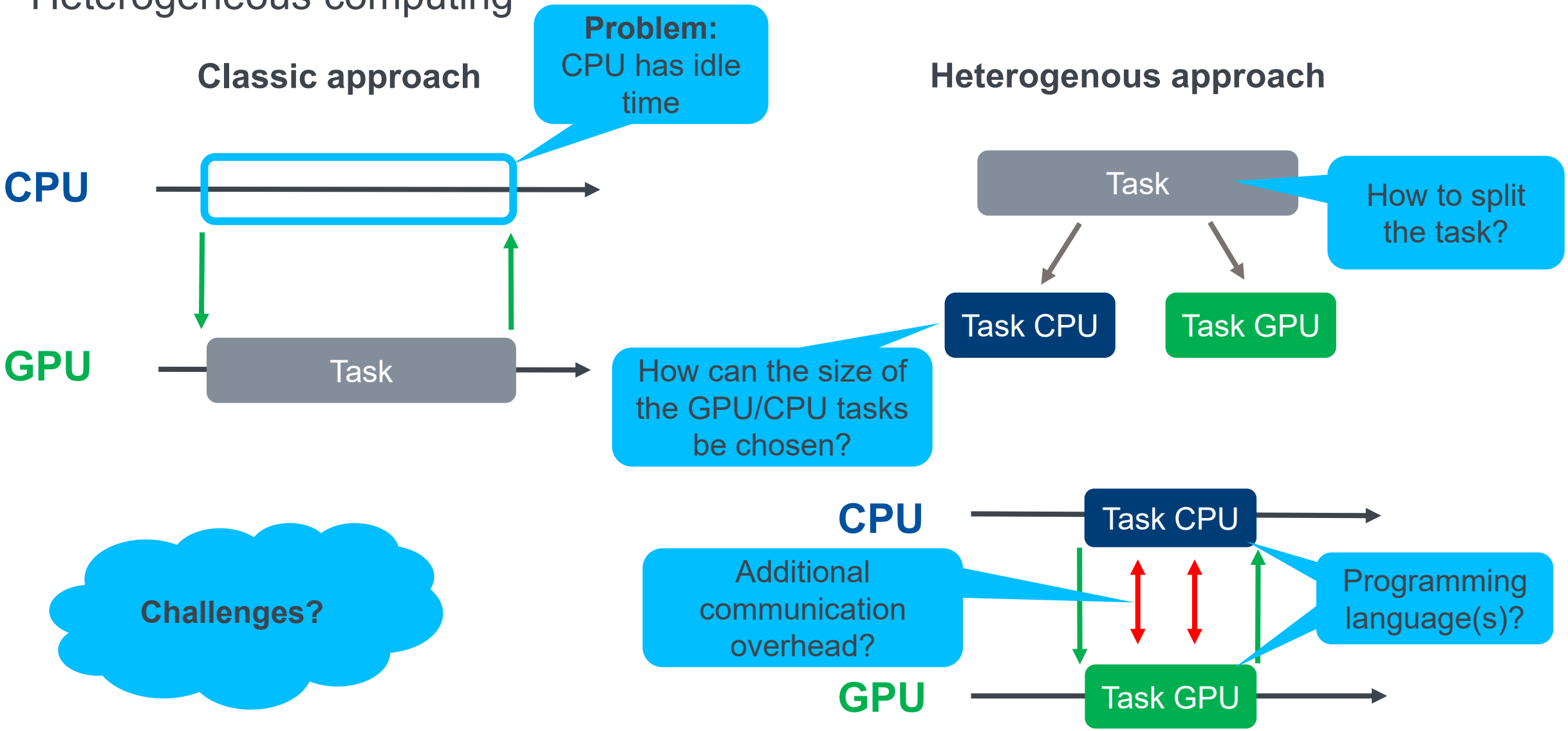

Goal

- Explore heterogeneous computing with CPU-GPU cooperation enabled through SYCL

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- Explore heterogeneous computing with CPU-GPU cooperation enabled through SYCL
- Heterogeneous implementation of solvers for linear systems with SPD matrices using SYCL
  - Conjugate Gradients algorithm
  - Cholesky factorization
  - Runtime comparison with CPU/GPU only implementations on various hardware including **NVIDIA, AMD, and Intel GPUs**

Conjugate Gradient Method

- Iteratively approximates solution of $Ax = b$ for SPD matrices A

While $\delta_{new} > \epsilon^2 \delta_0$ do:

$\mathrm{q} = \mathrm{Ad}$

$\alpha = \frac{\delta_{new}}{d^T \mathrm{q}}$

$\mathrm{x} = \mathrm{x} + \alpha \mathrm{d}$

$\mathrm{r} = \mathrm{b} - \alpha \mathrm{q}$

$\delta_{old} = \delta_{new}$

$\delta_{new} = \mathrm{r}^T \mathrm{r}$

$\beta = \frac{\delta_{new}}{\delta_{old}}$

$\mathrm{d} = \mathrm{r} + \beta \mathrm{d}$

Matrix-Vector operations

Vector-Vector operations

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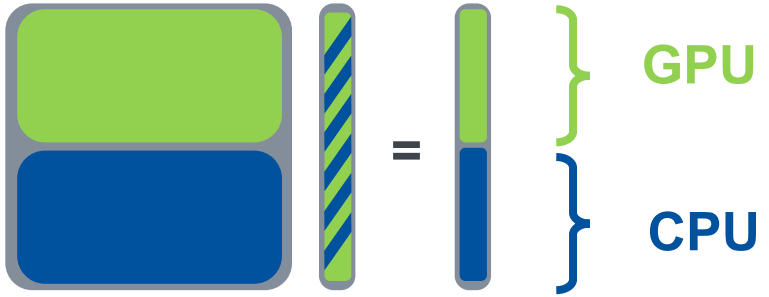

Vector-Vector operations

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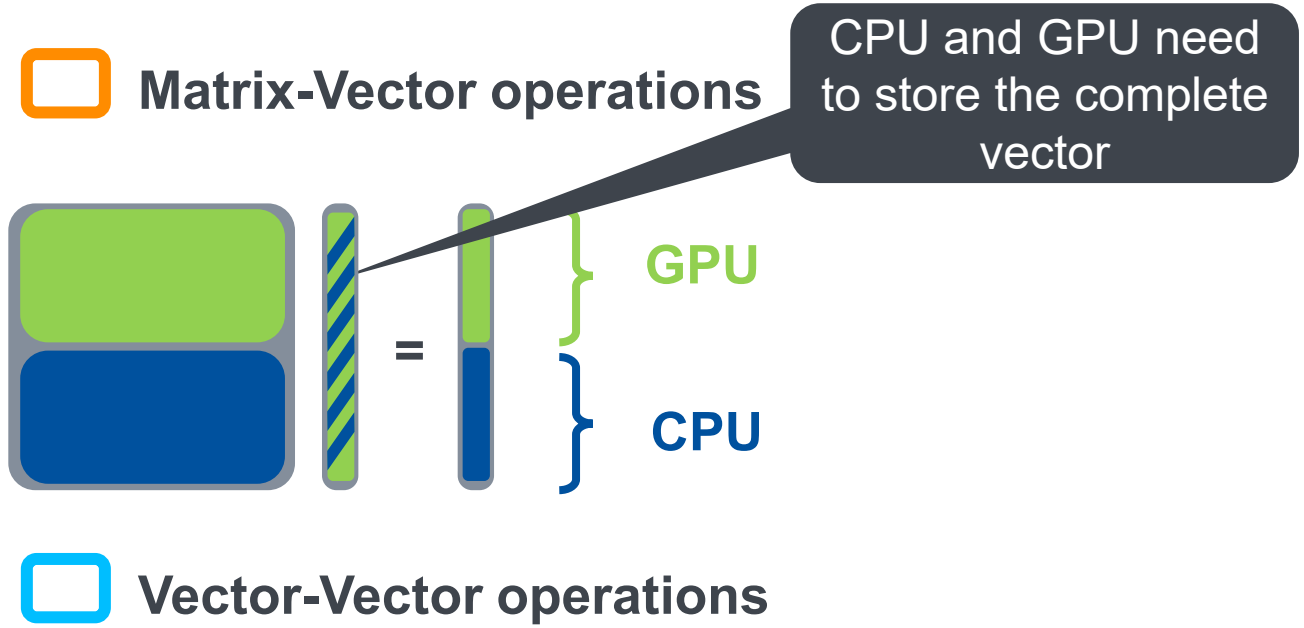

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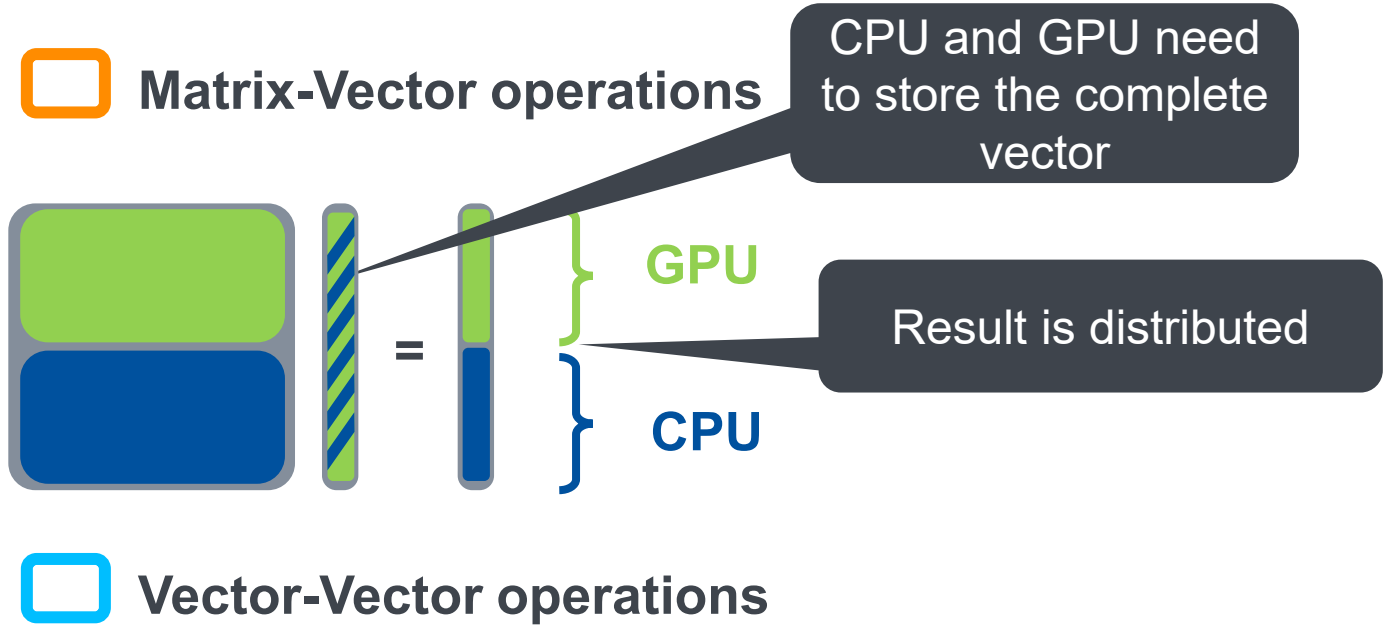

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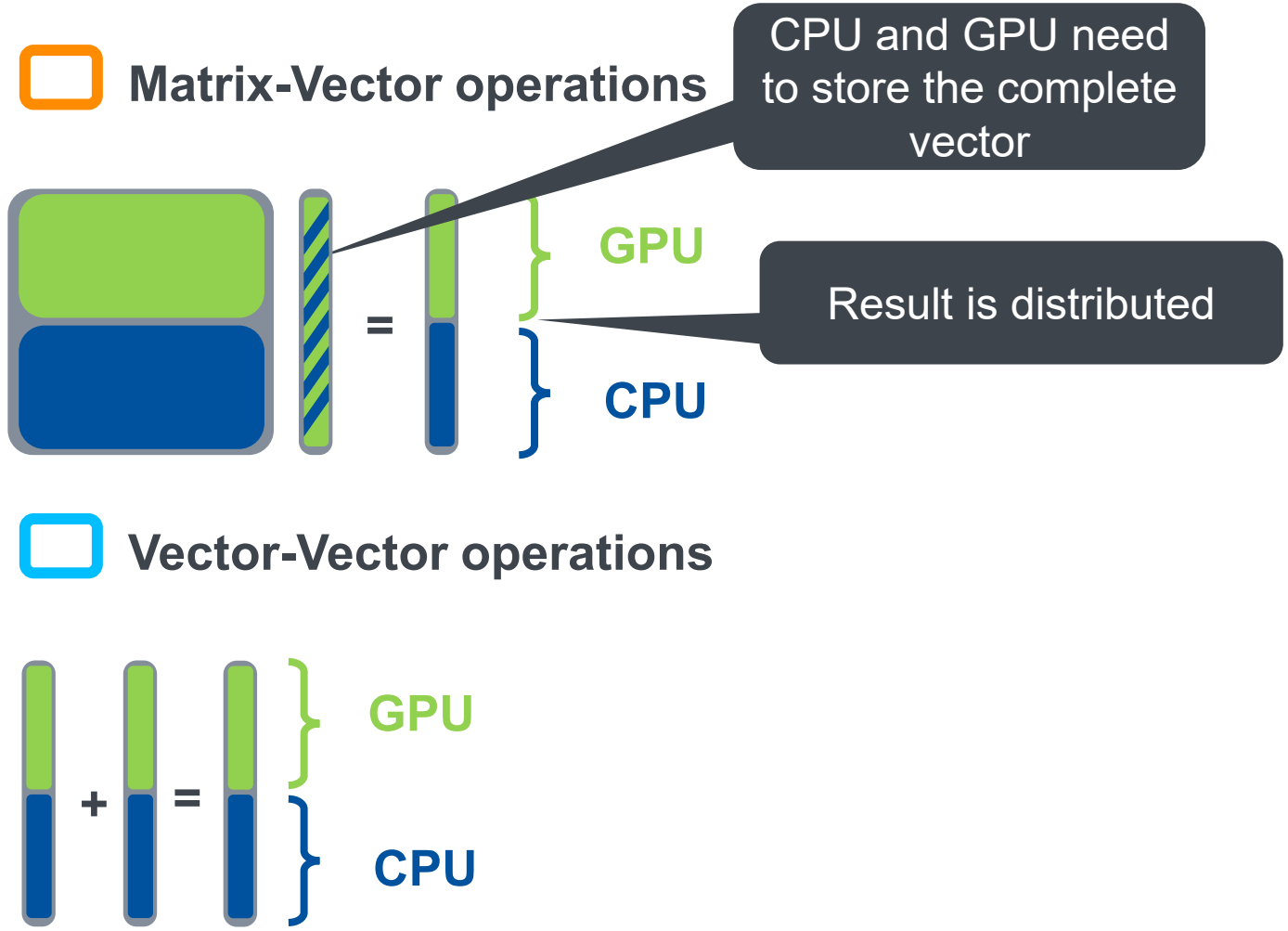

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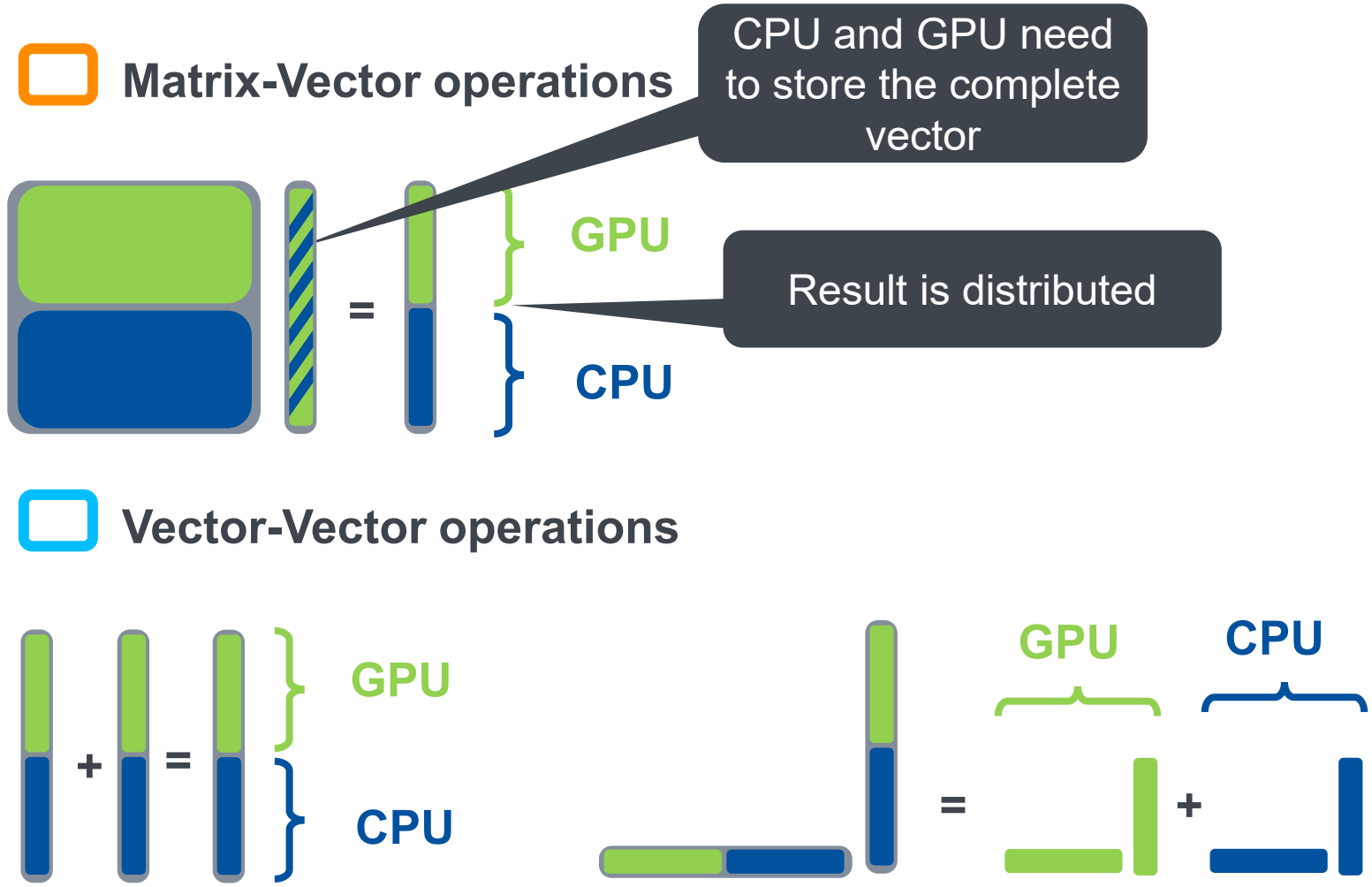

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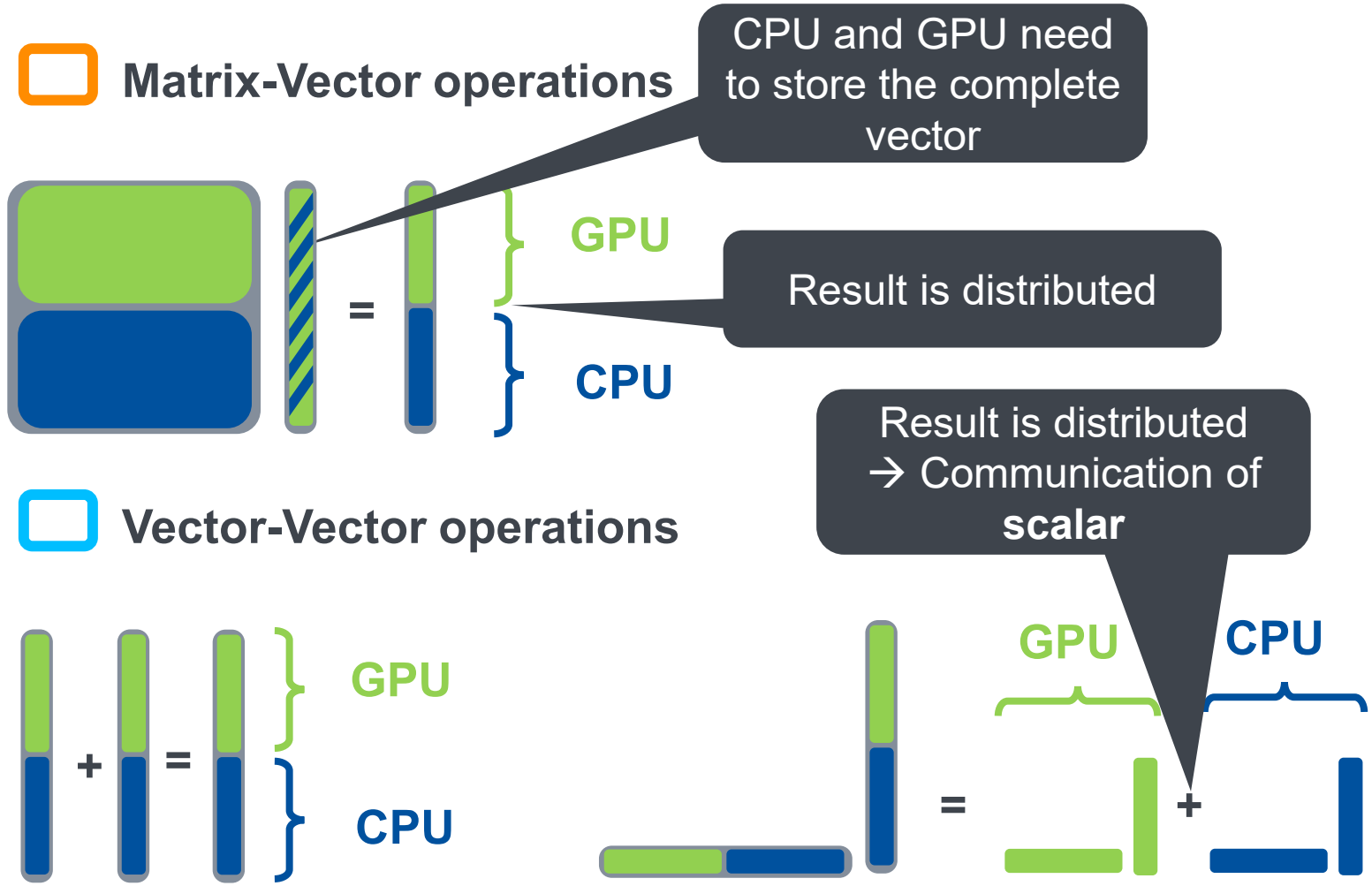

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$q = Ad$

$\alpha = \frac{\delta_{new}}{d^T q}$ **Scalar Com.**

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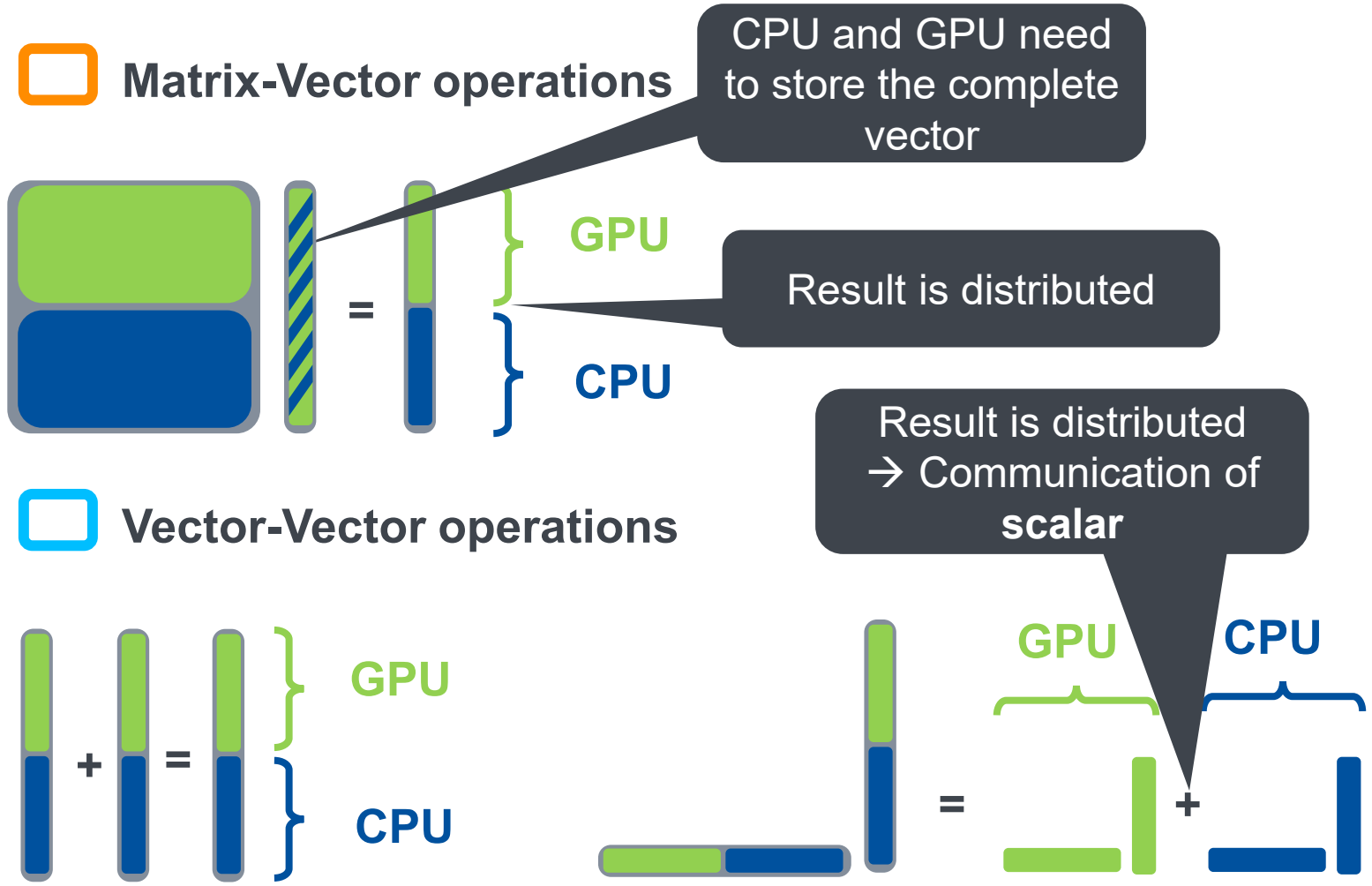

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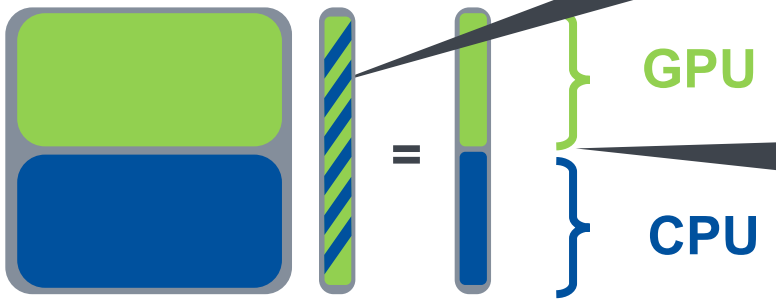
Vector Com. of d

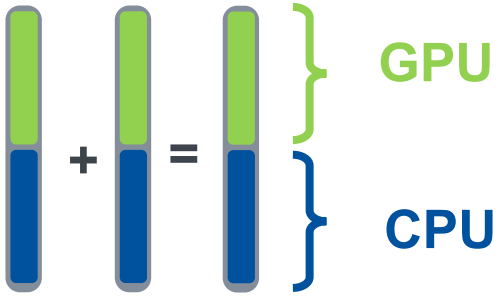
Matrix-Vector operations



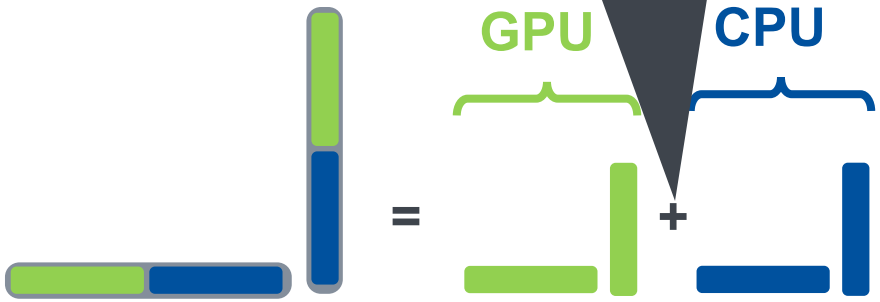
CPU and GPU need to store the complete vector

Result is distributed

Vector-Vector operations



Result is distributed → Communication of **scalar**



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Cholesky – blocked algorithm

- Factorizes an SPD matrix A into a lower triangular matrix L with $A = LL^T$

for k = 0…N-1

A_{kk} = Cholesky(A_{kk})

for m = k+1…N-1

A_{mk} = solve(A_{kk}, A_{mk})

for m = k+1…N-1

$A_{mm} \mathrel{-}= A_{mk} \cdot A_{mk}^{\mathsf{T}}$

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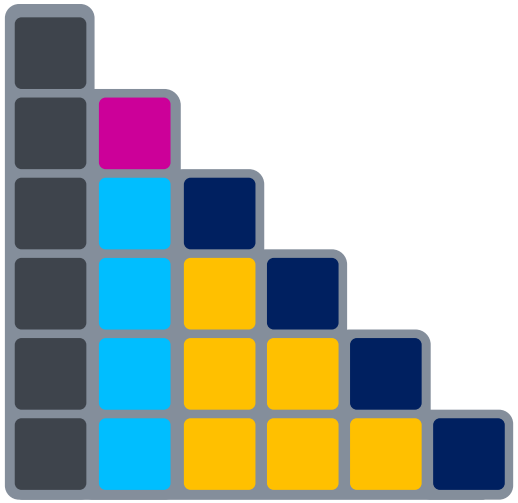

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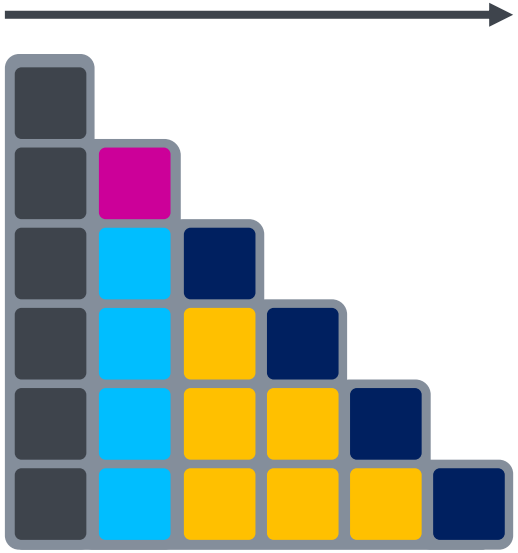

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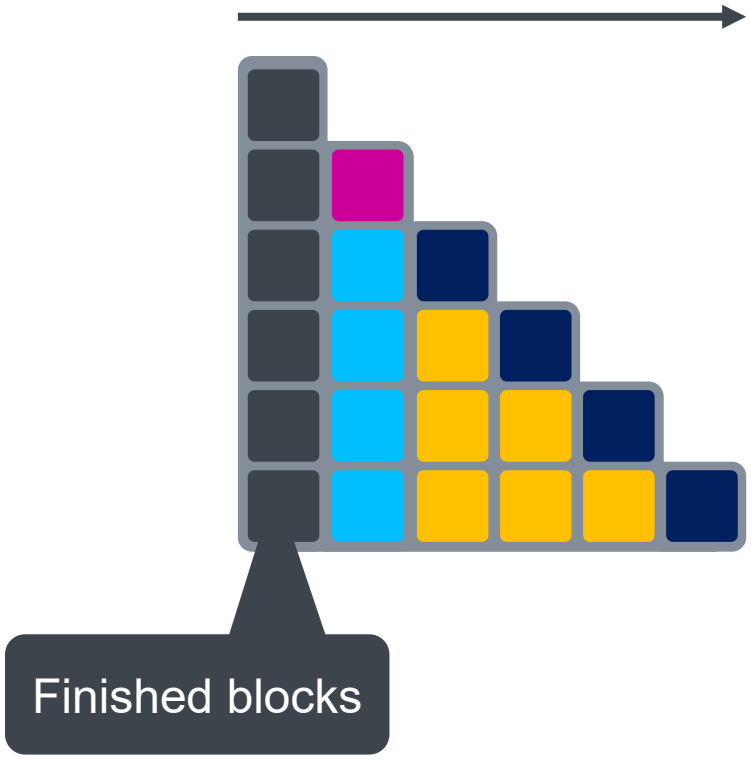

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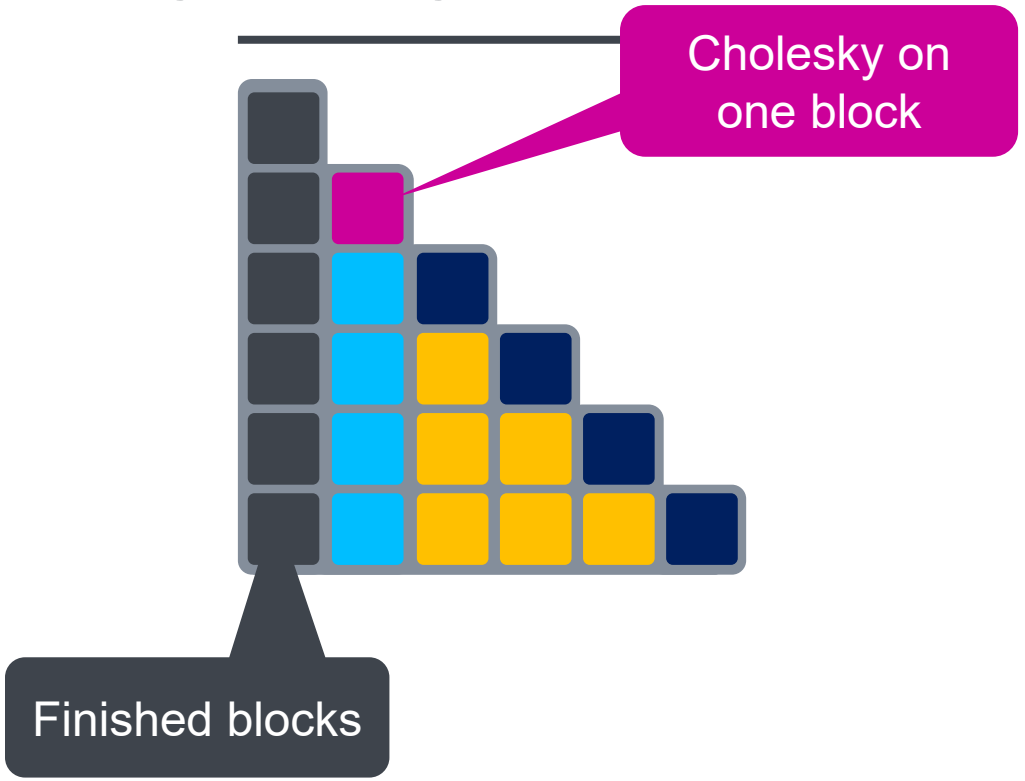

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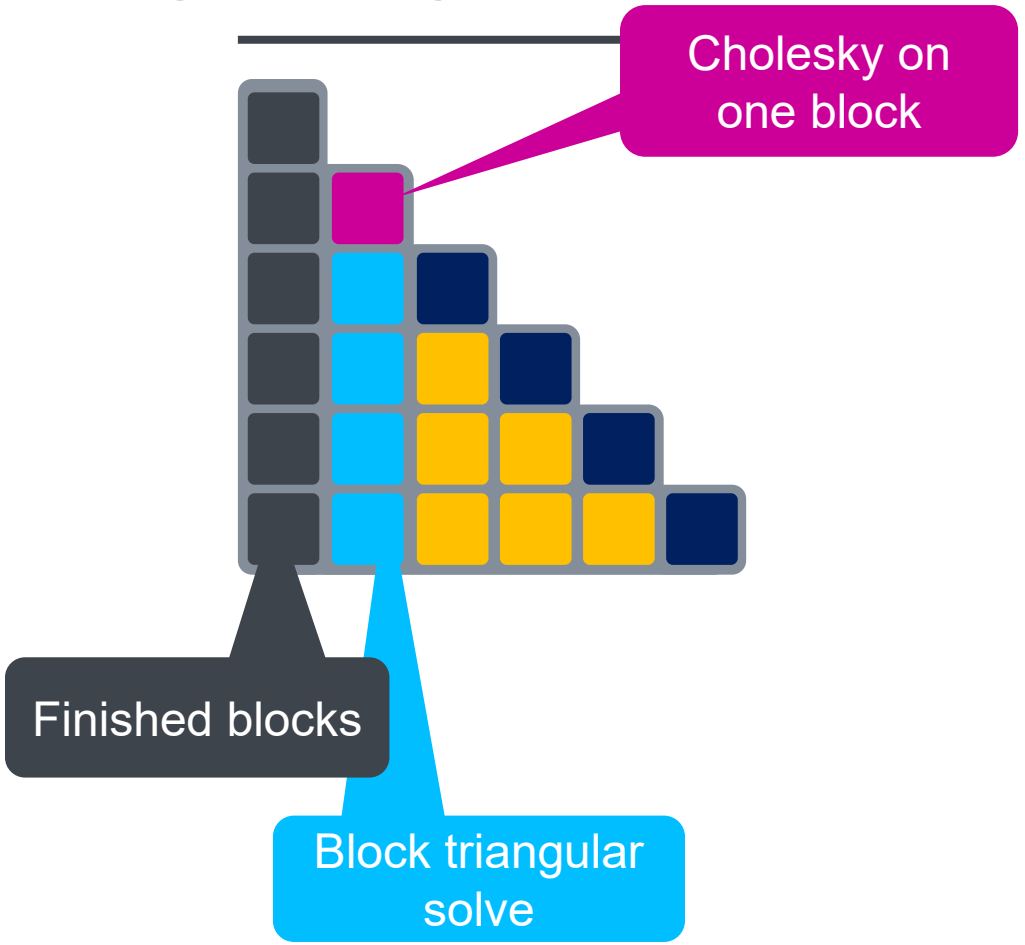

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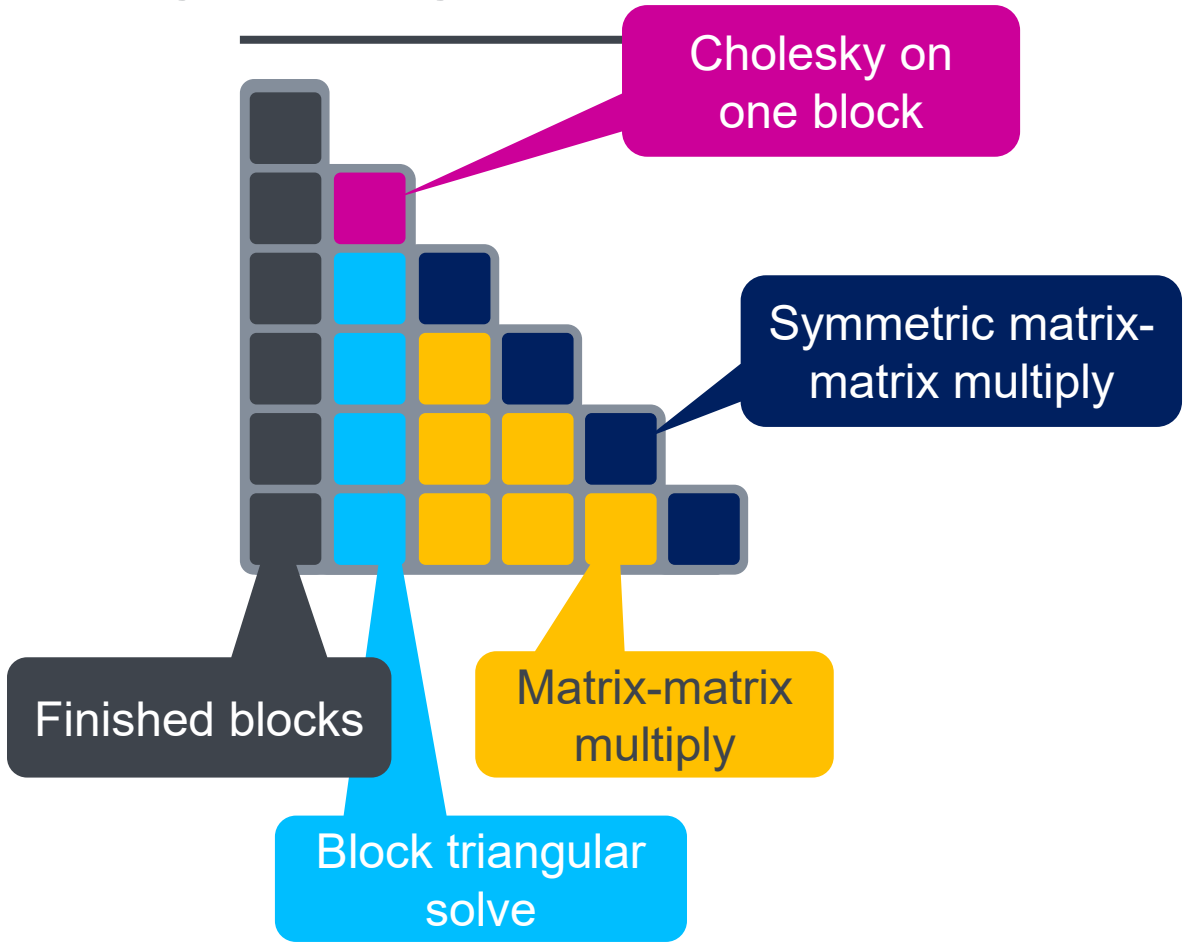

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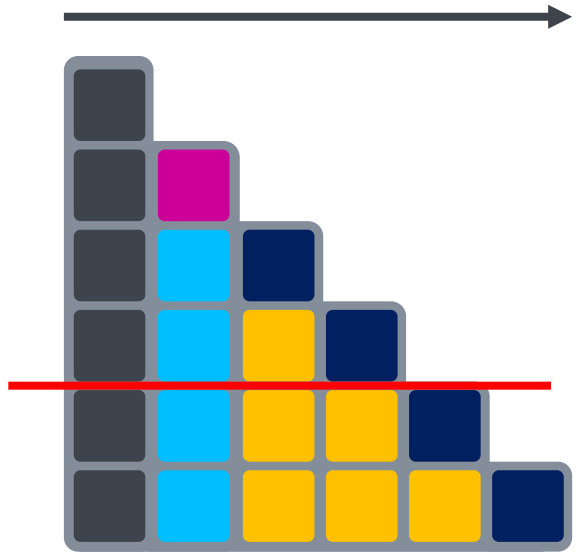

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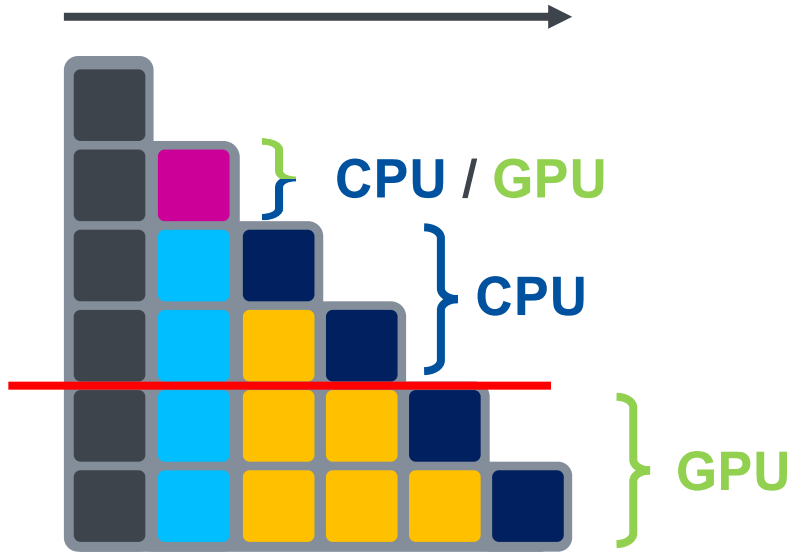

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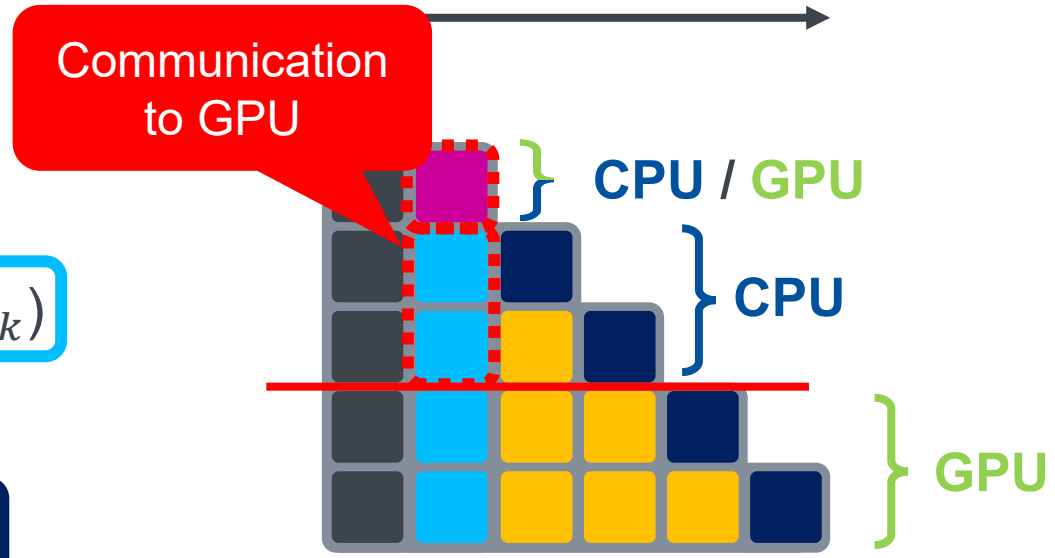

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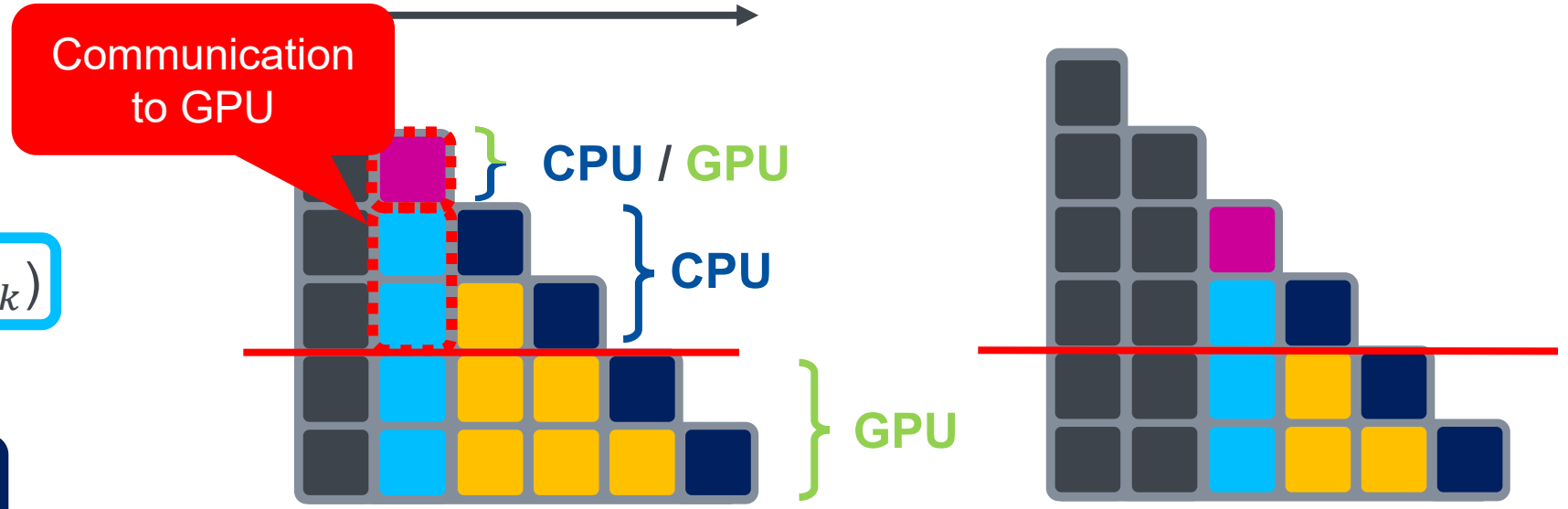
Right-looking: one column after another



Cholesky – blocked algorithm

- Factorizes an SPD matrix A into a lower triangular matrix L with $A = LL^T$

for k = 0…N-1

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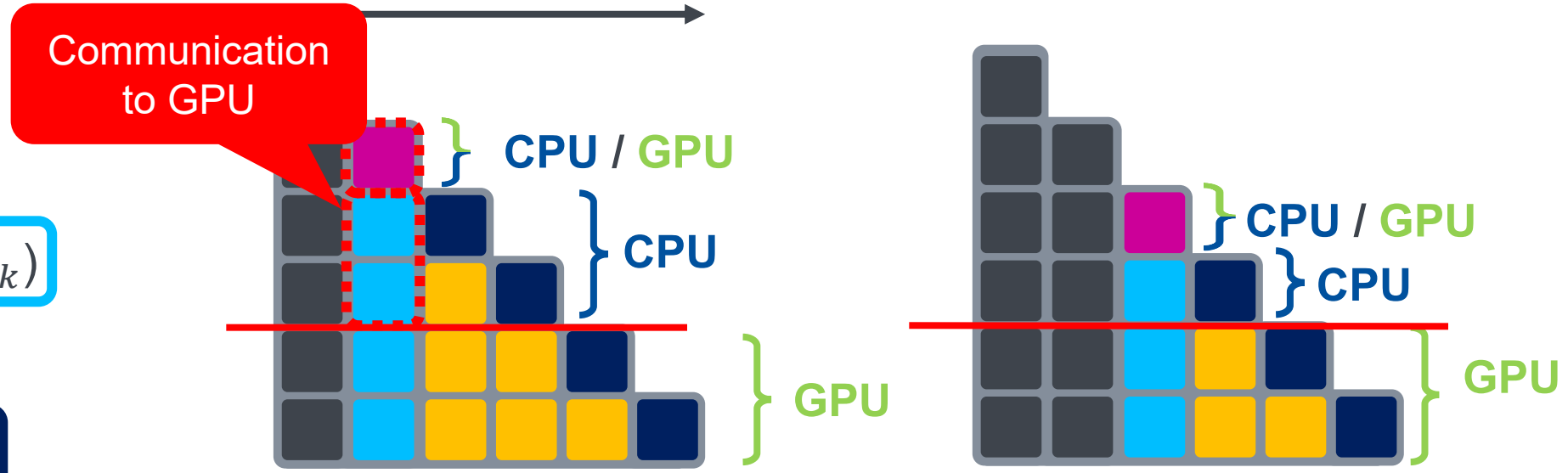

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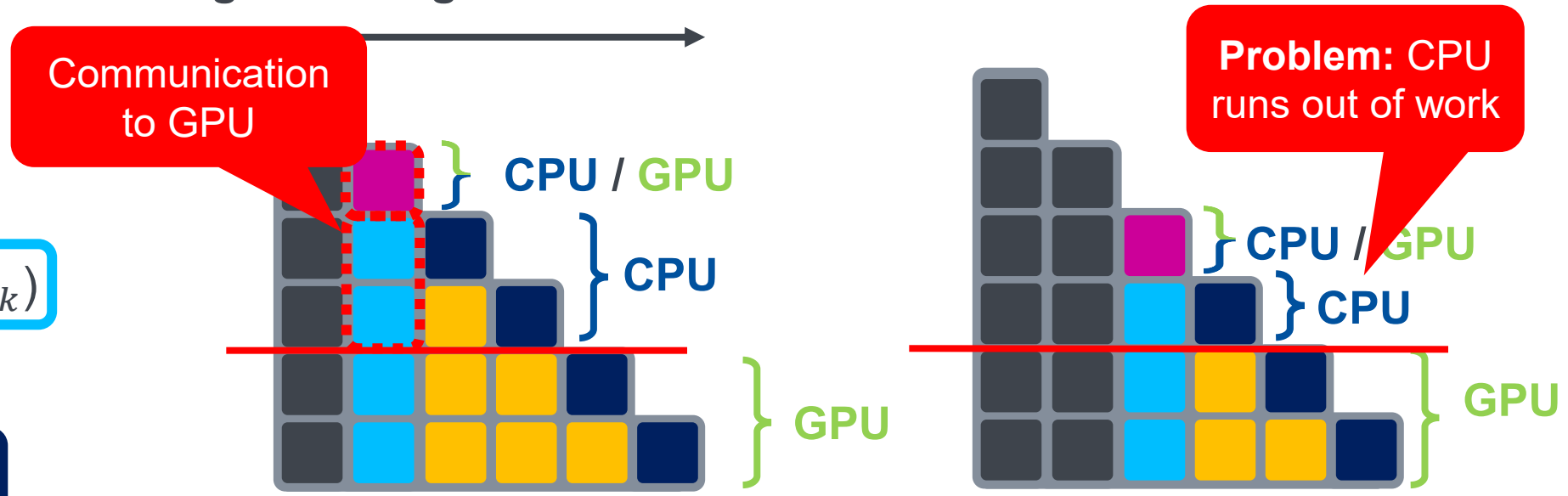

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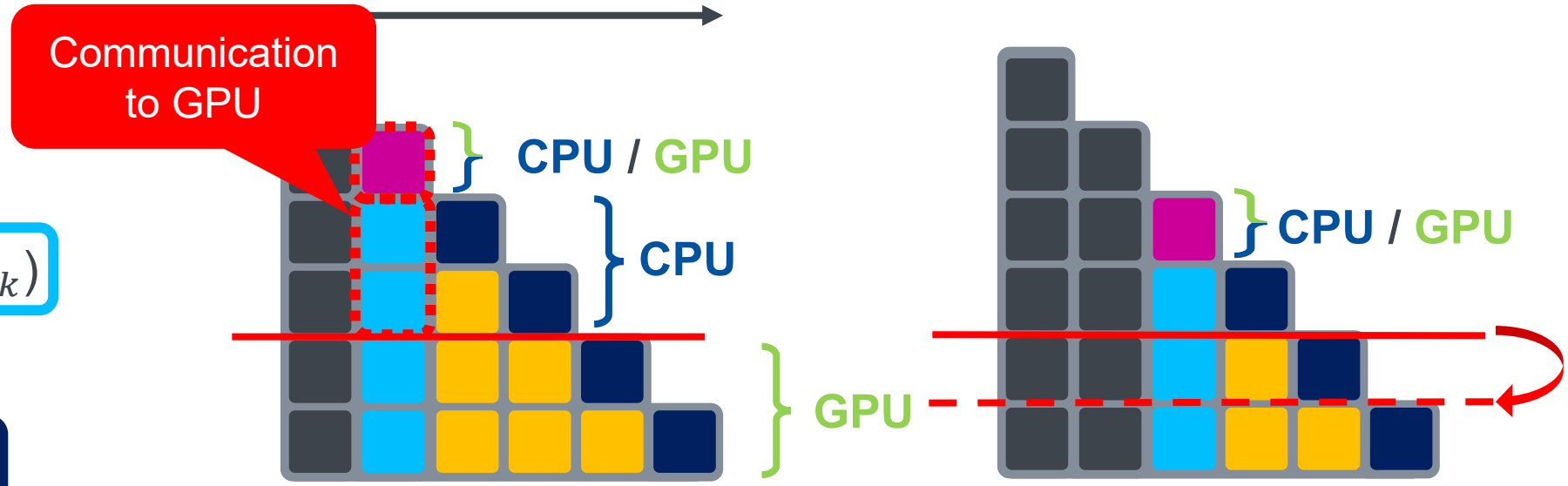

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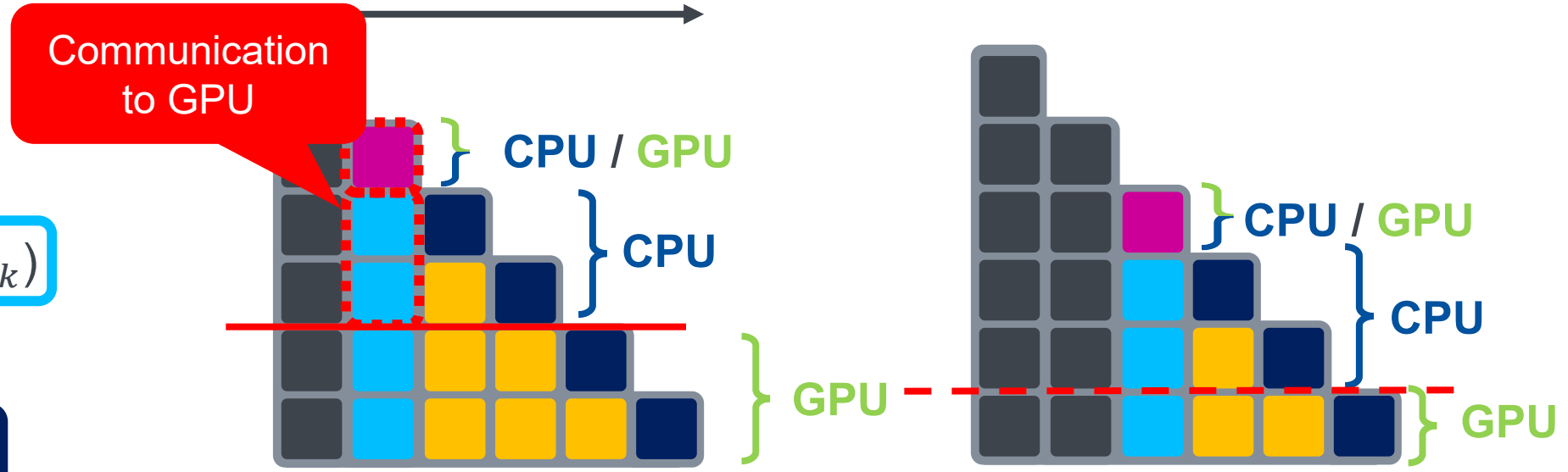

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Conjugate Gradients and Cholesky

CG

Cholesky

Conjugate Gradients and Cholesky

CG

- Iterative solver to approximate the result

Cholesky

- Direct solver that produces exact solution

Conjugate Gradients and Cholesky

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How does heterogeneous computing affect the runtime of the two algorithms?

Experimental Setup

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- Solving large systems of linear equations with dense kernel matrices obtained from simulation data for Gaussian Process Regression [2]
  - Sizes $2^{12} \times 2^{12}$ to $2^{16} \times 2^{16}$
- Results for two main Systems are shown:

[2] Helmann, Maksim, Alexander Strack, and Dirk Pflüger. 2025. “Replication Data for: GPRat: Gaussian Process Regression with Asynchronous Tasks.” DaRUS. https://doi.org/doi:10.18419/DARUS-4743.

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Runtime Evaluation: Heterogeneous CG Algorithm

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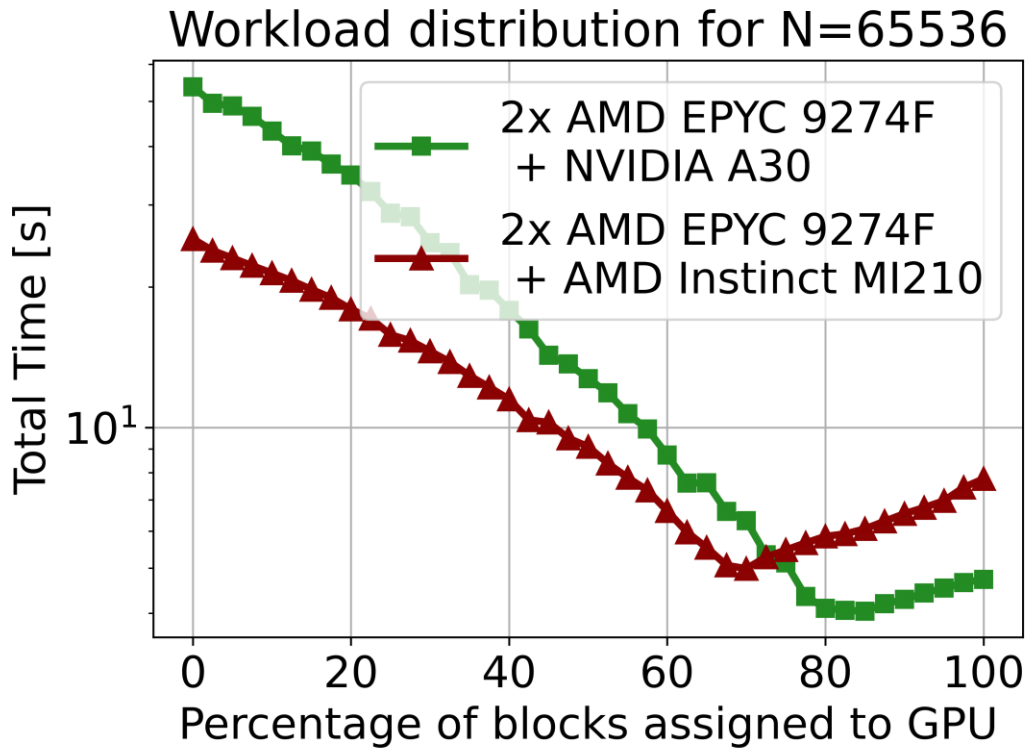

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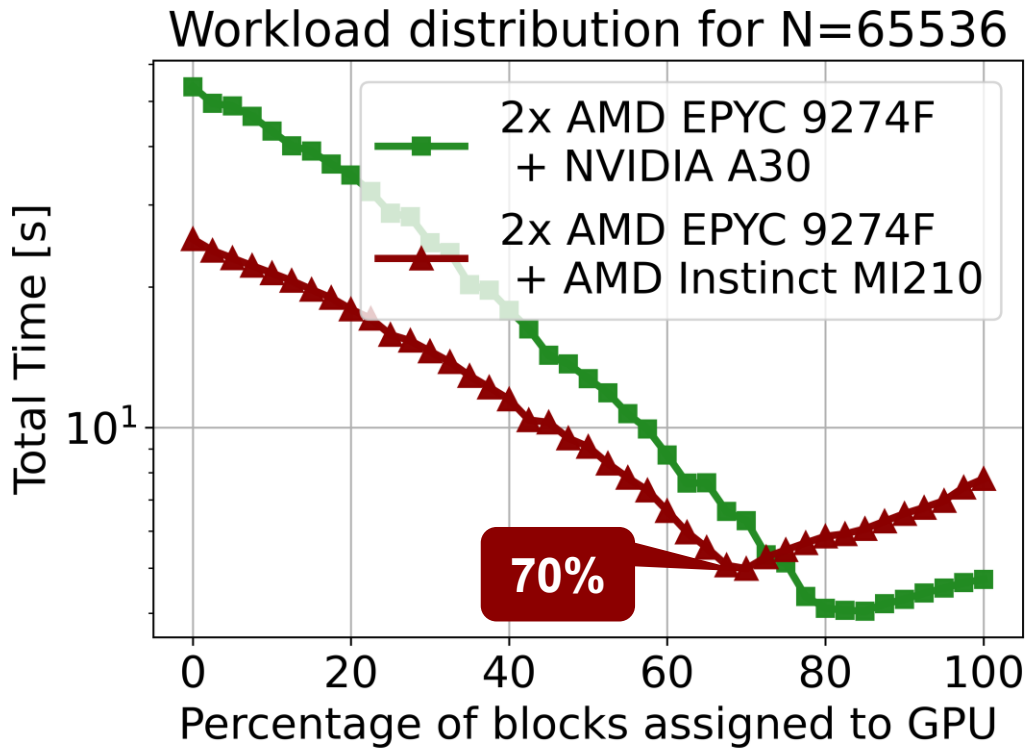

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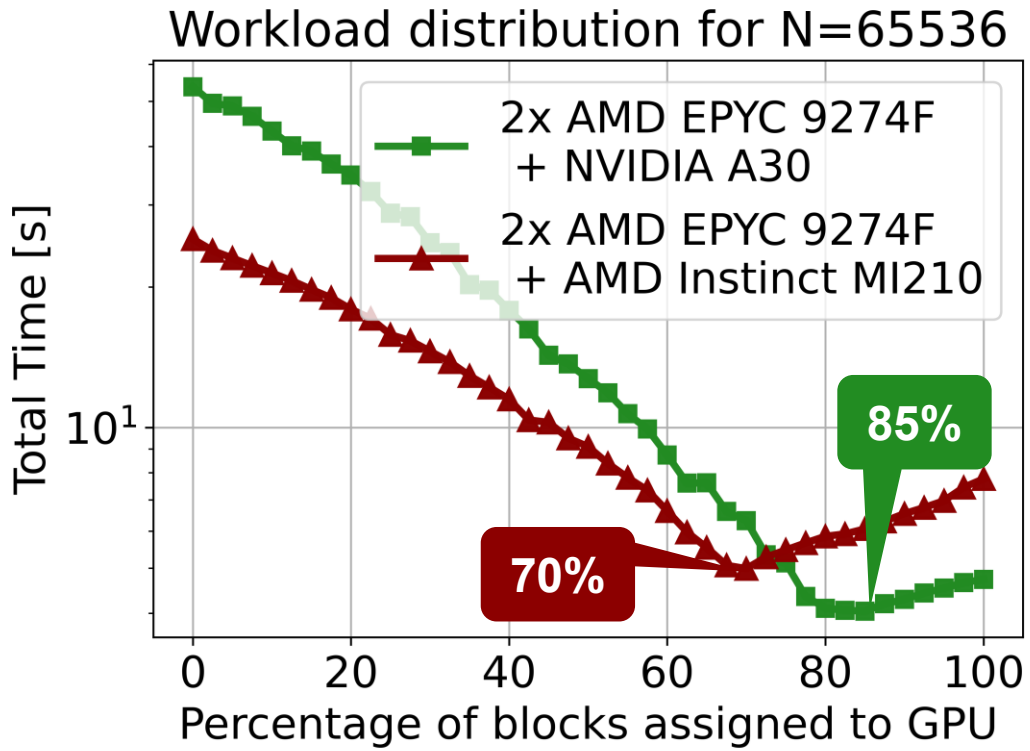

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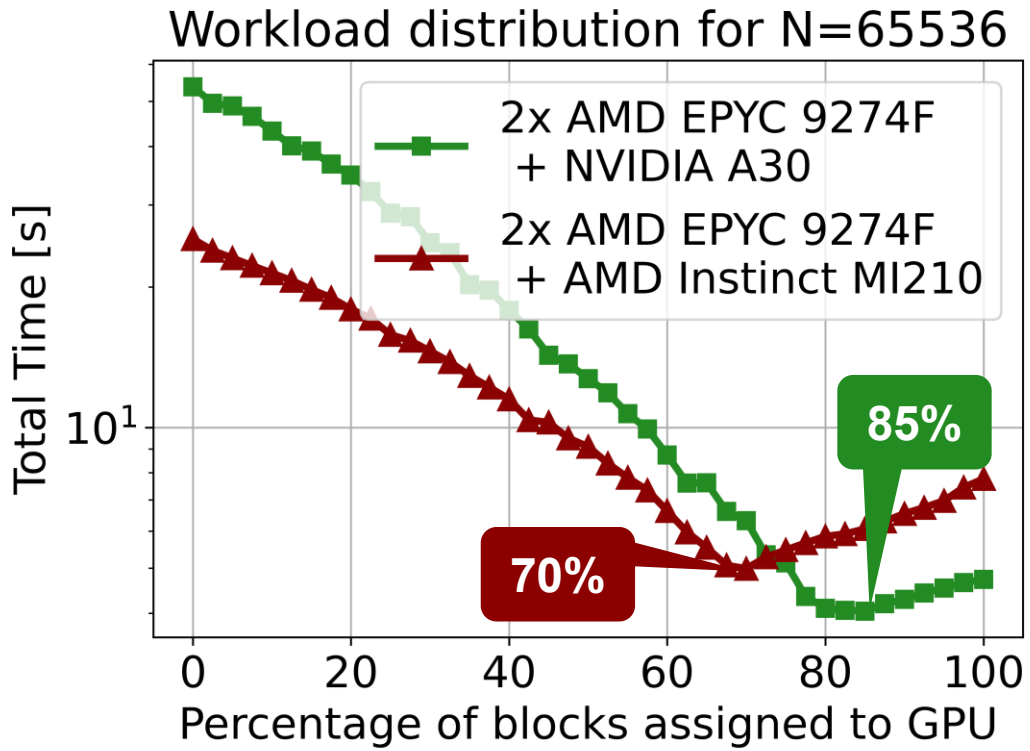

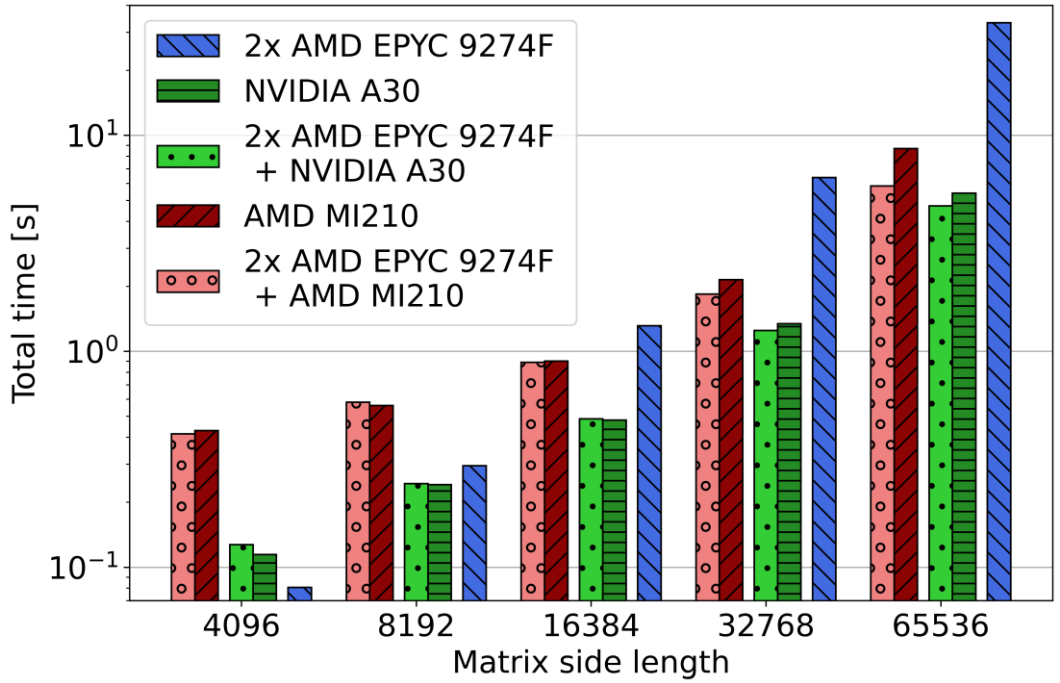

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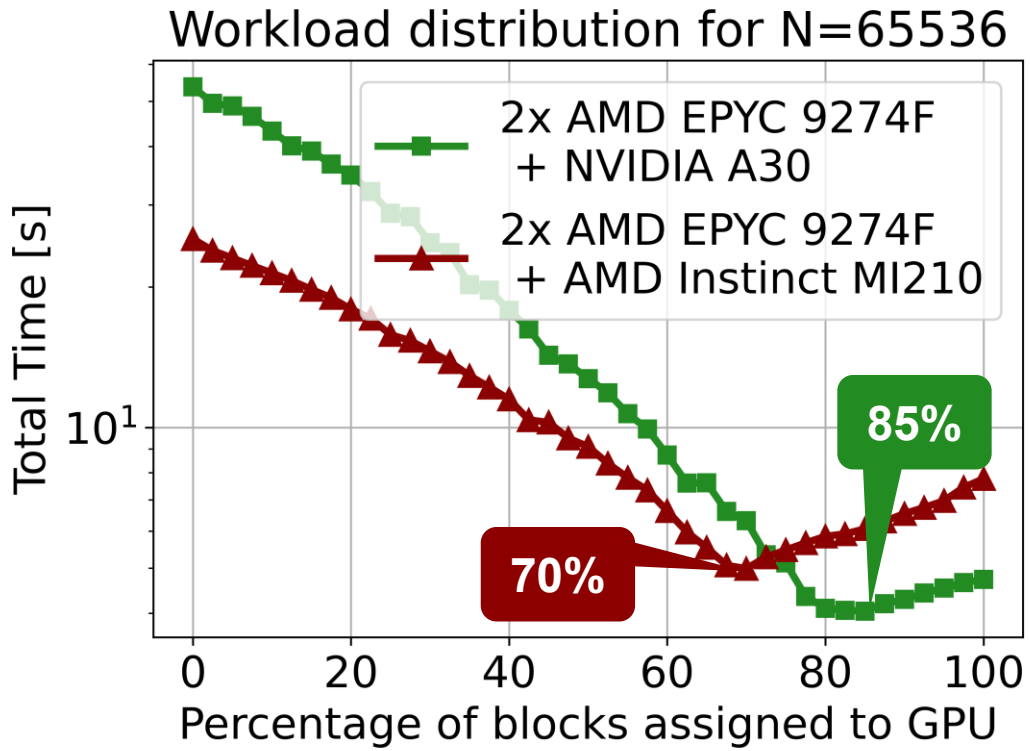

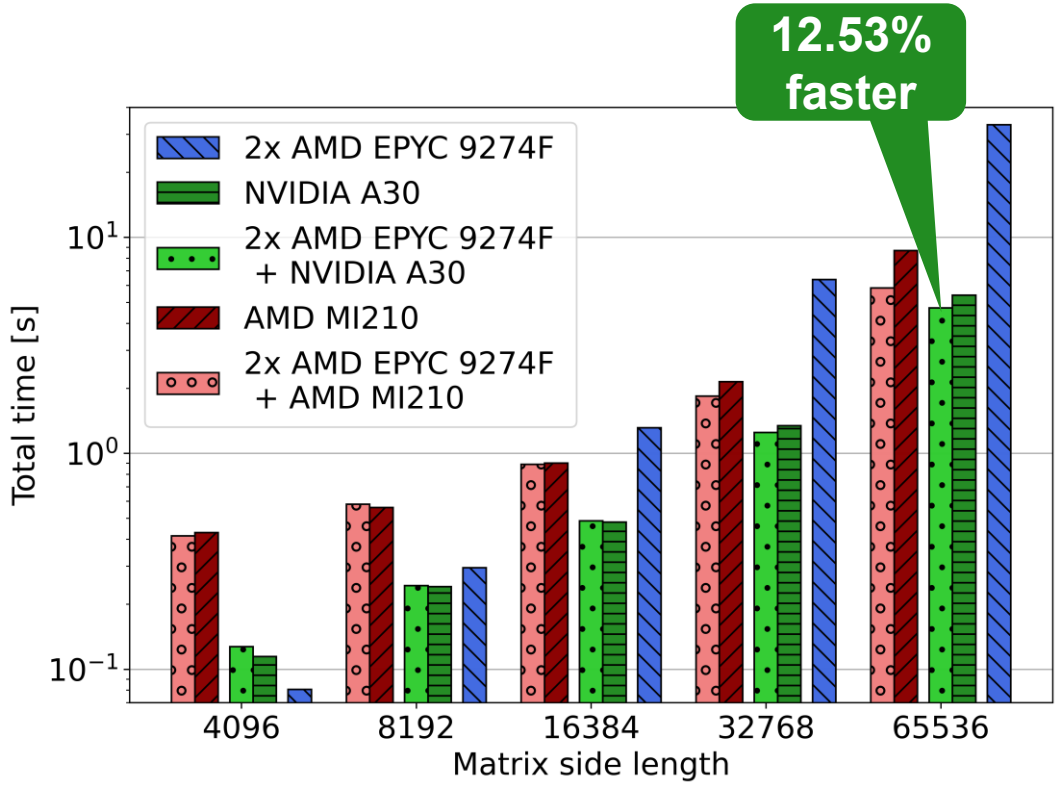

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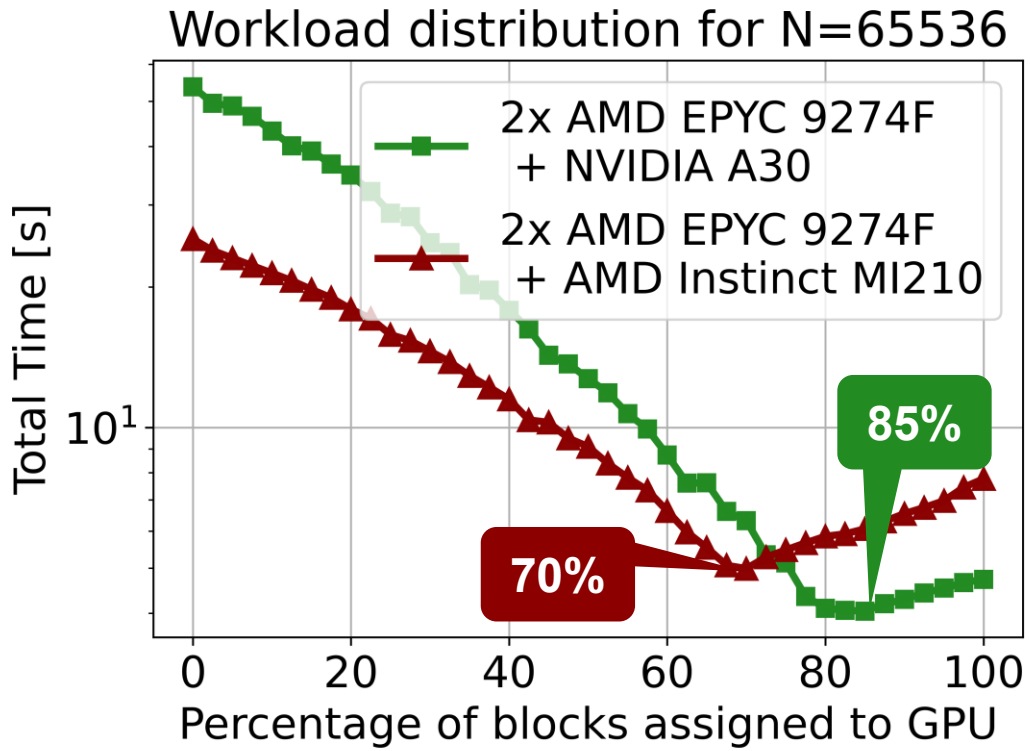

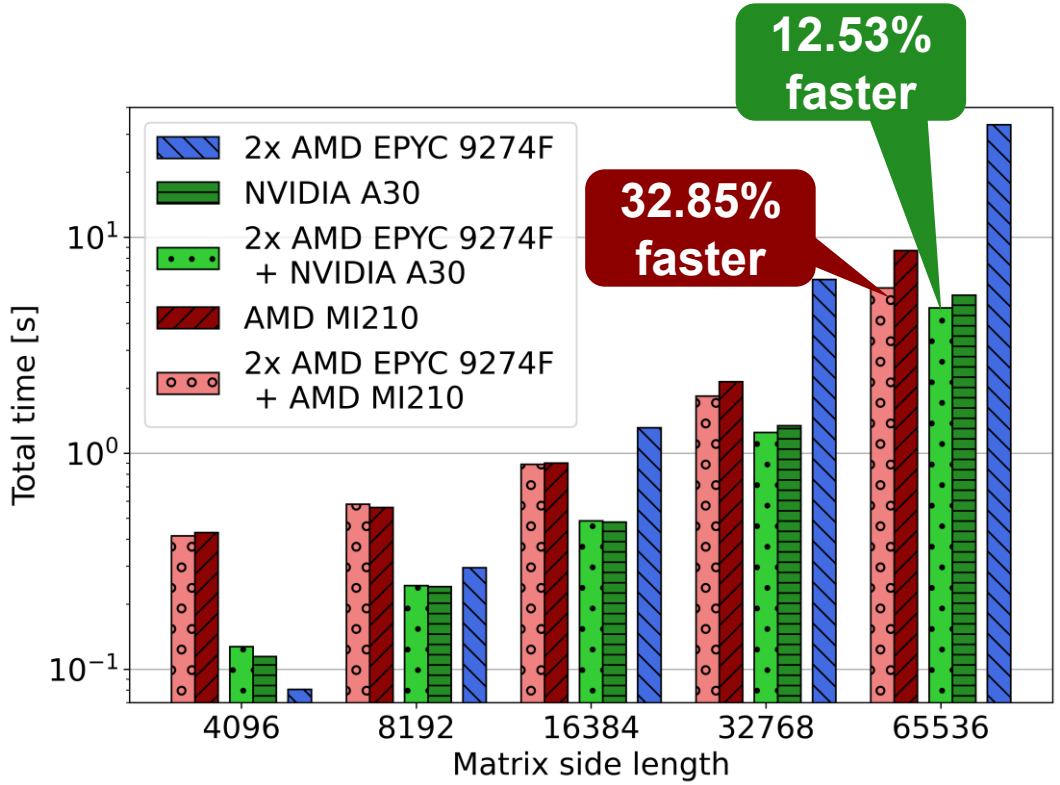

CG Algorithm: Comparison of Intel icpx and AdaptiveCpp

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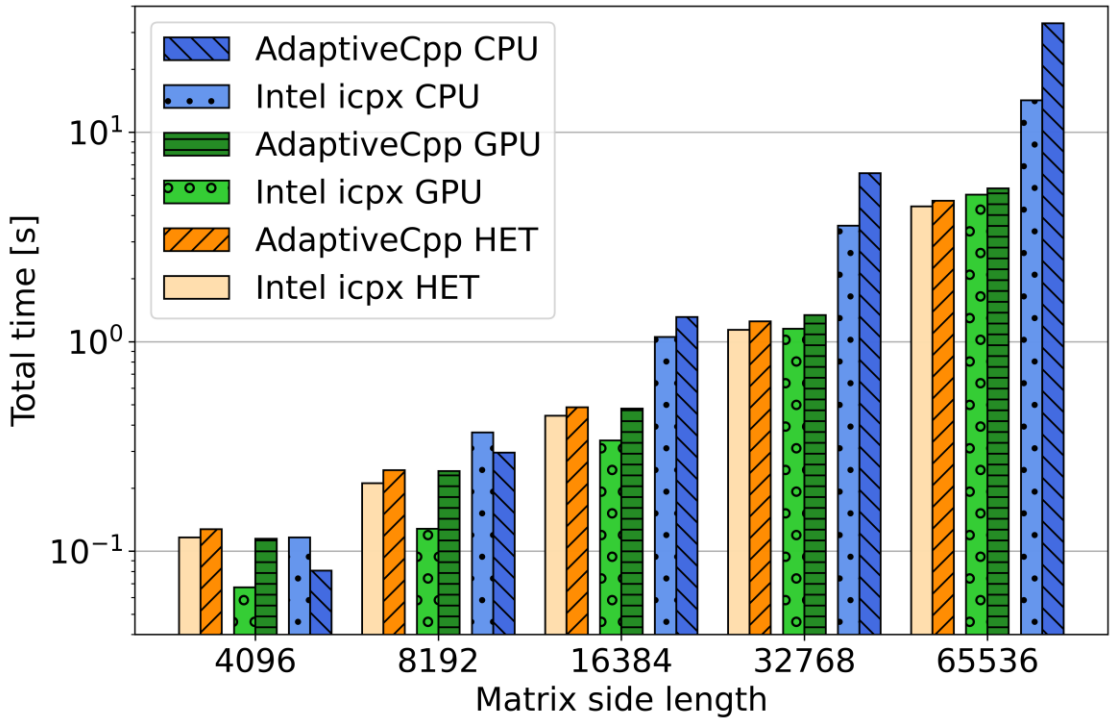

System 1 (NVIDIA A30)

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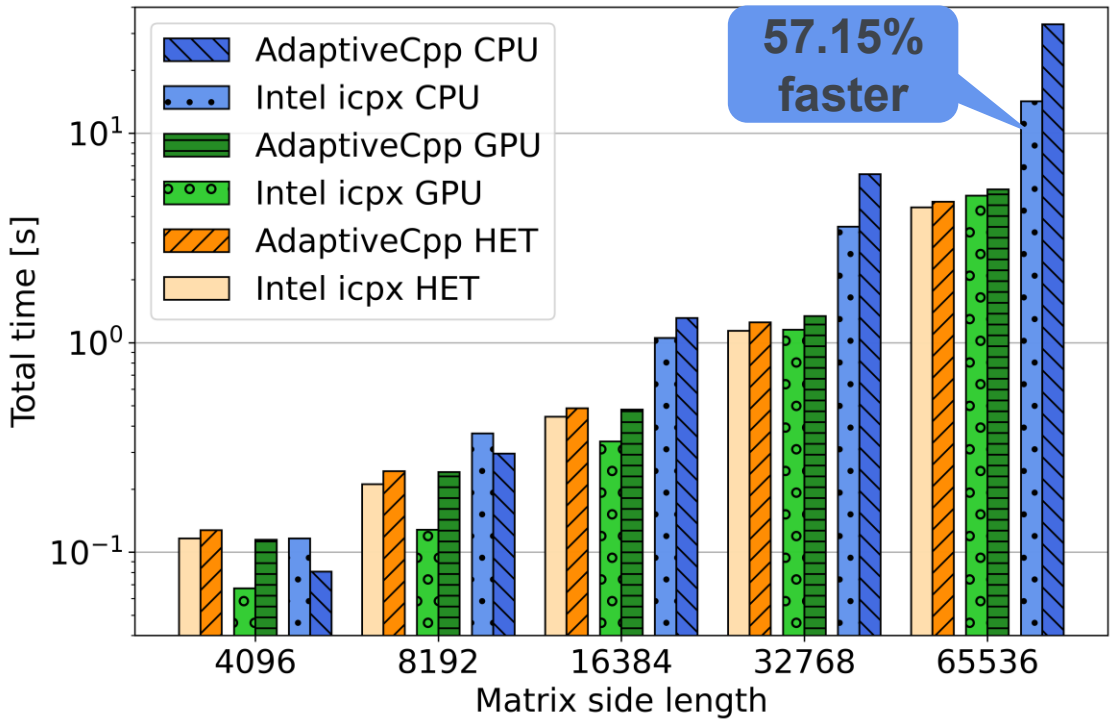

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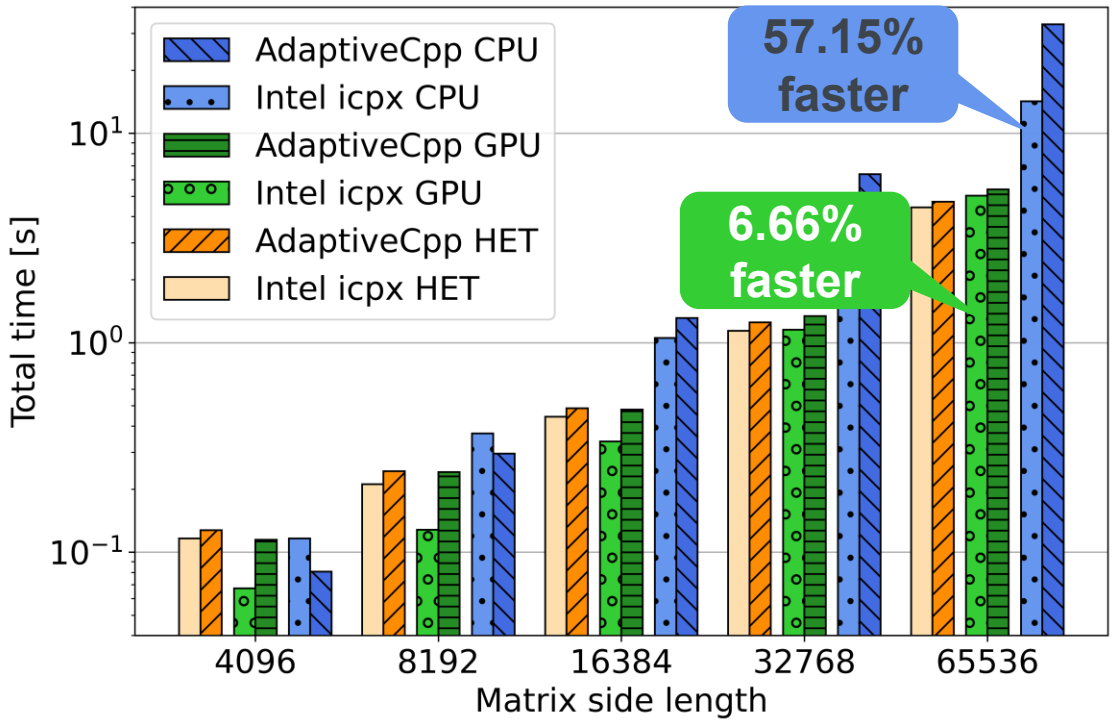

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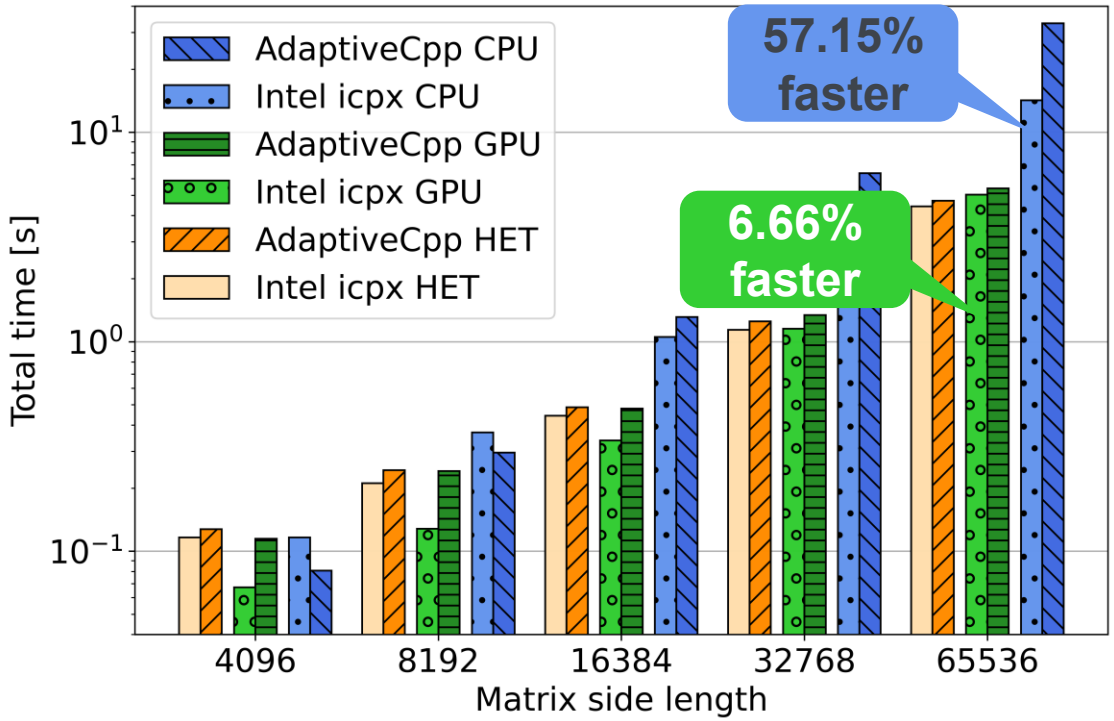

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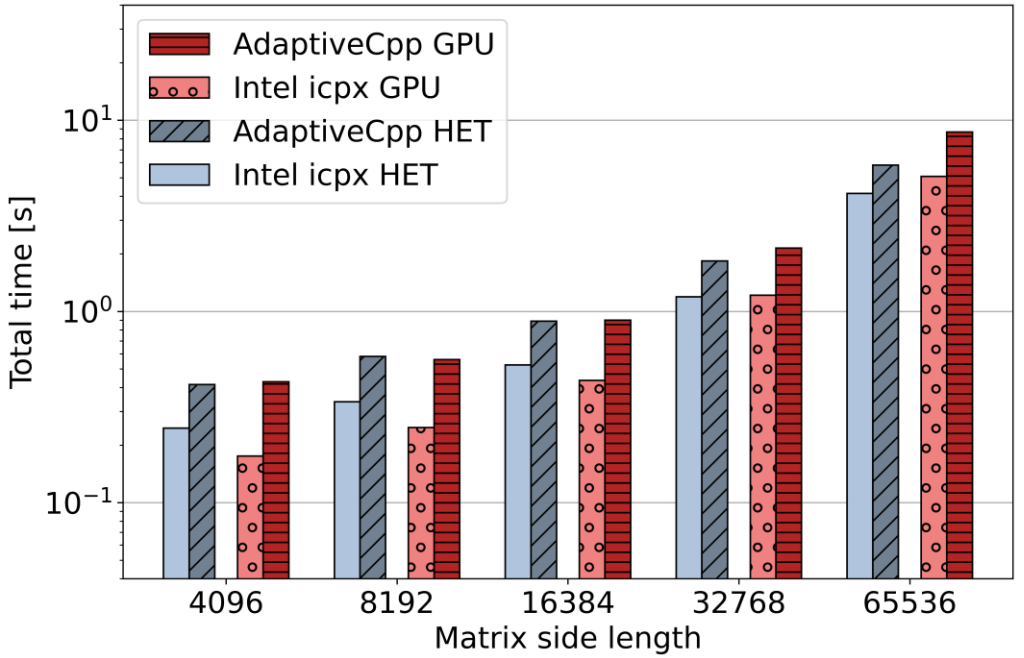

System 2 (AMD MI210)

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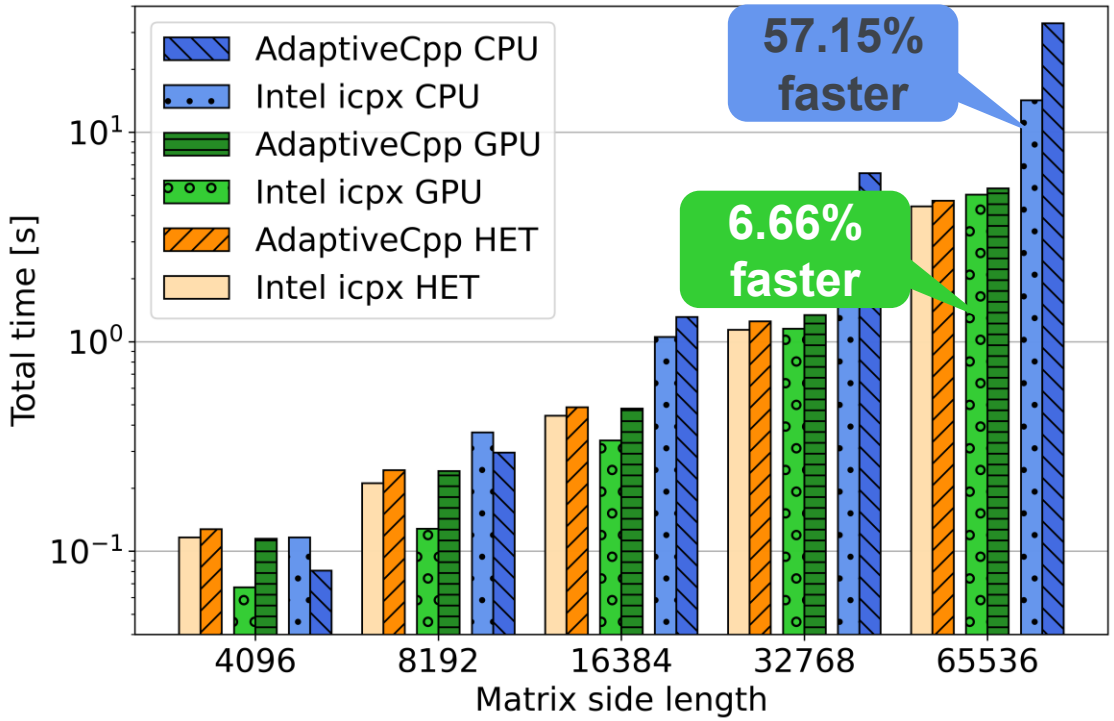

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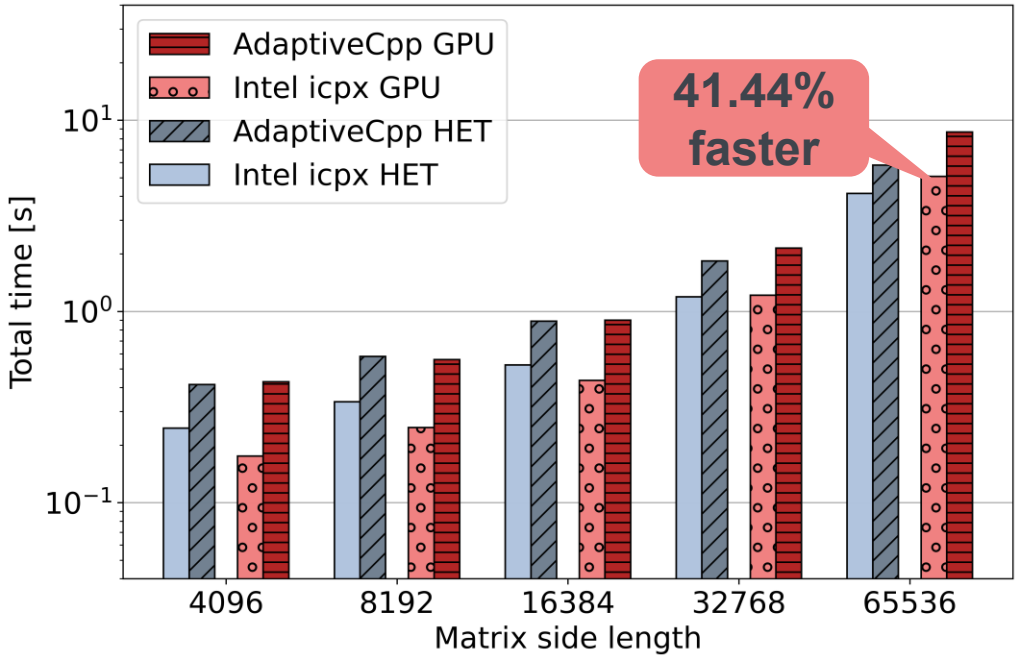

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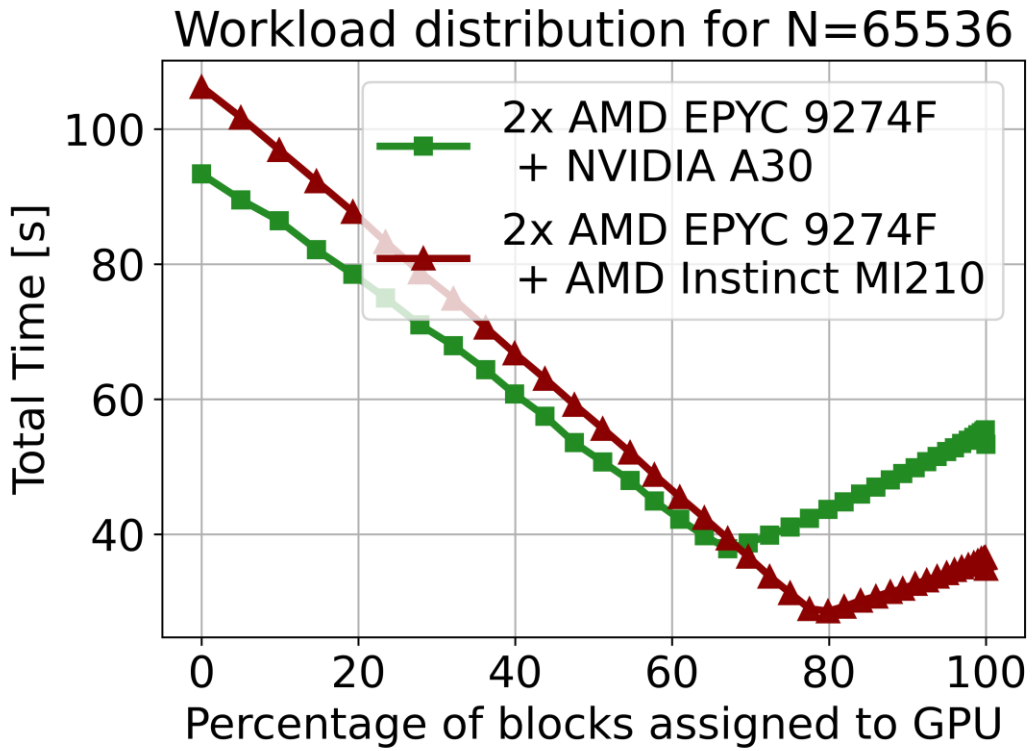

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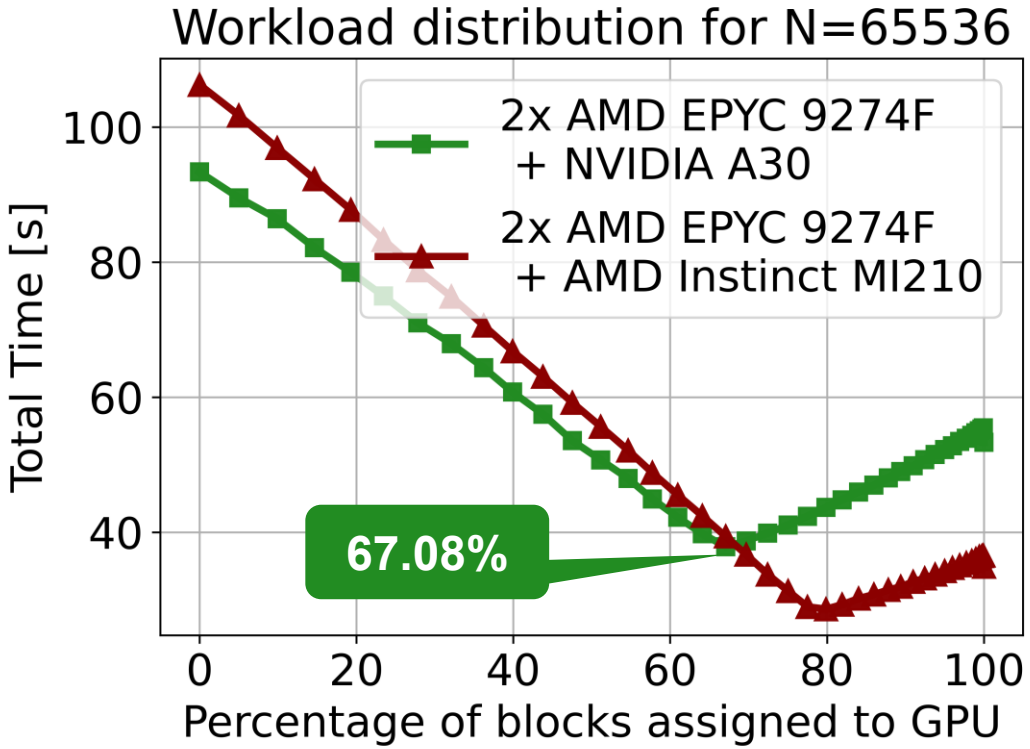

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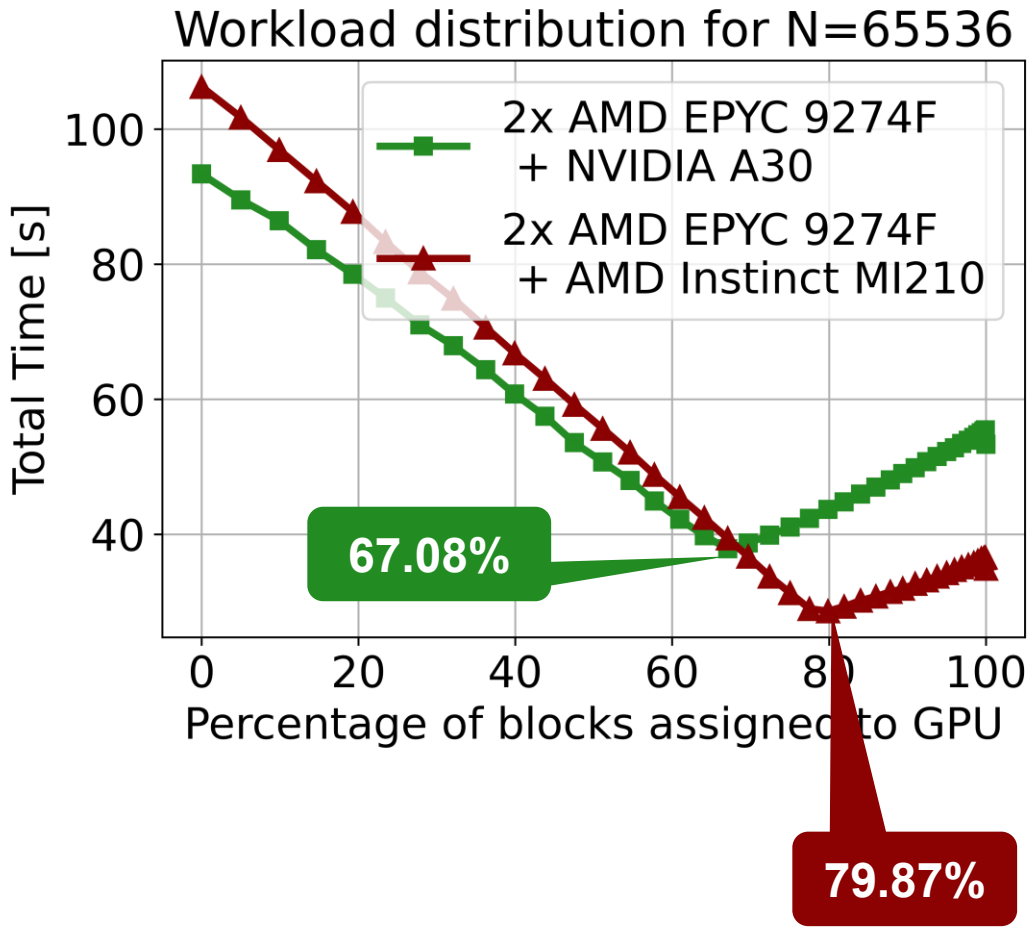

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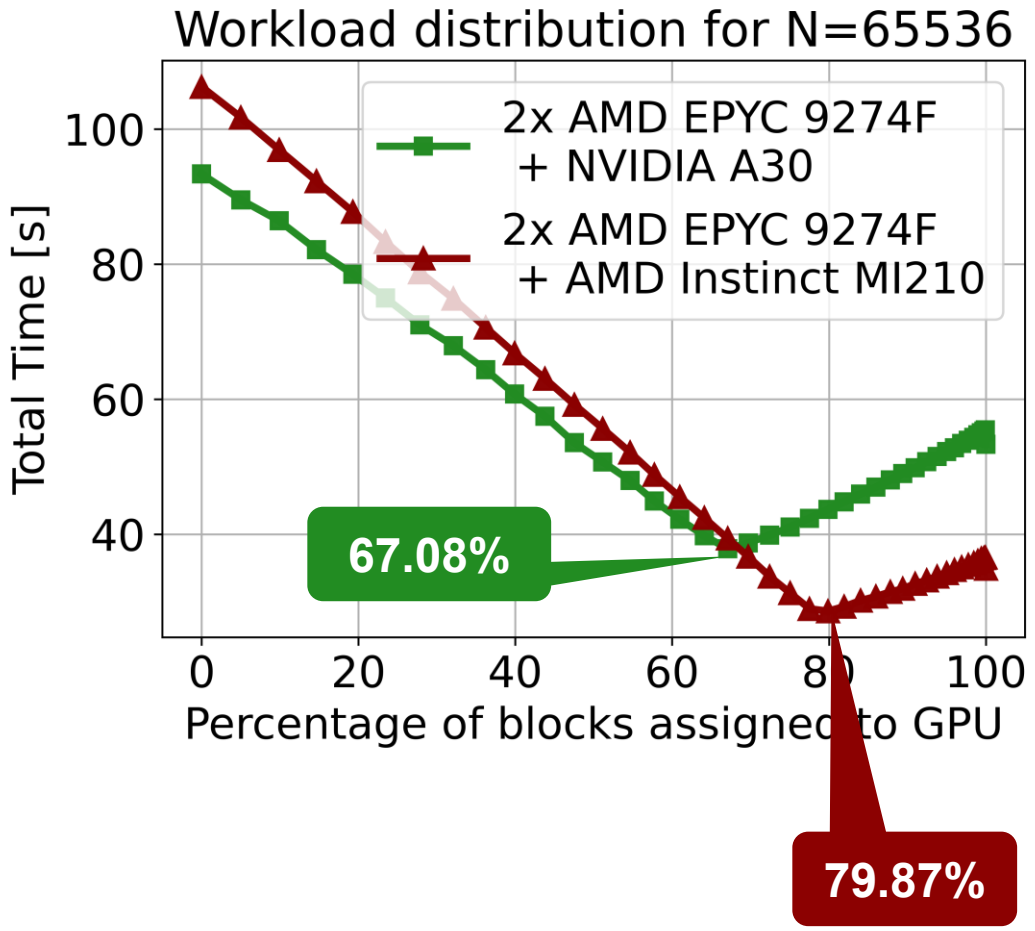

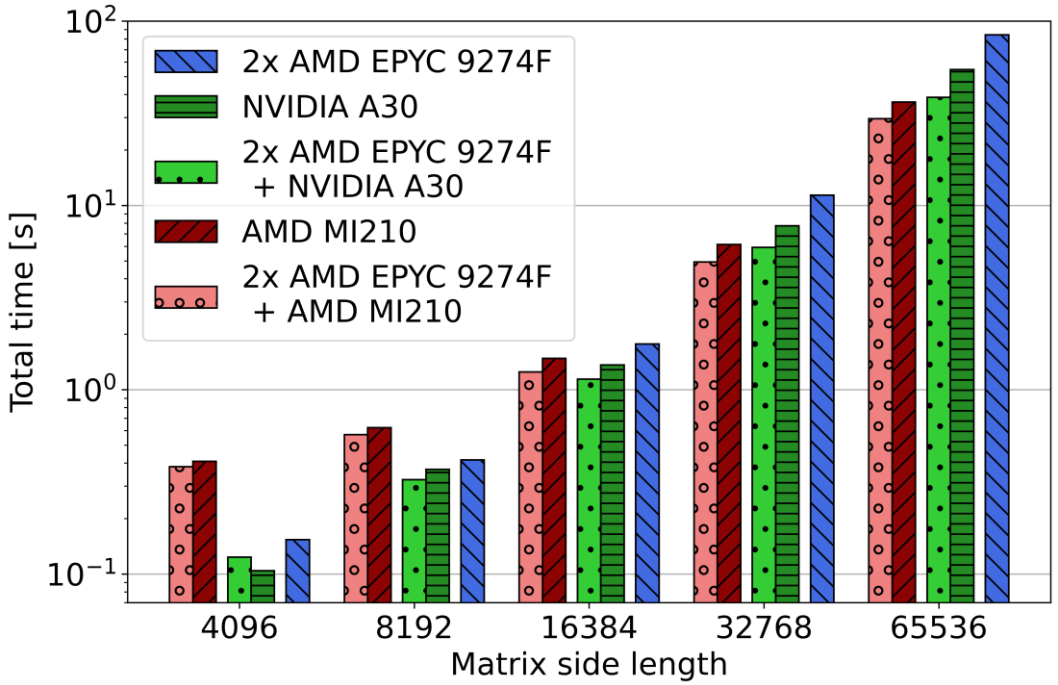

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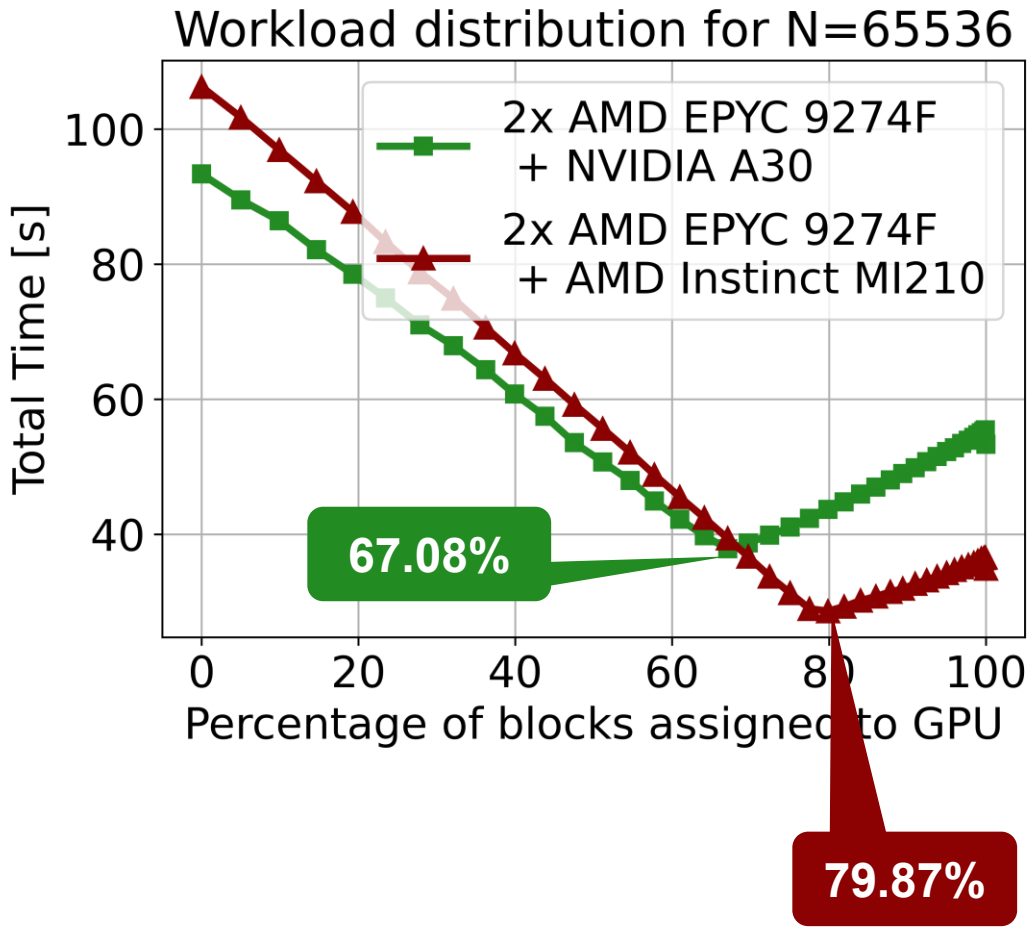

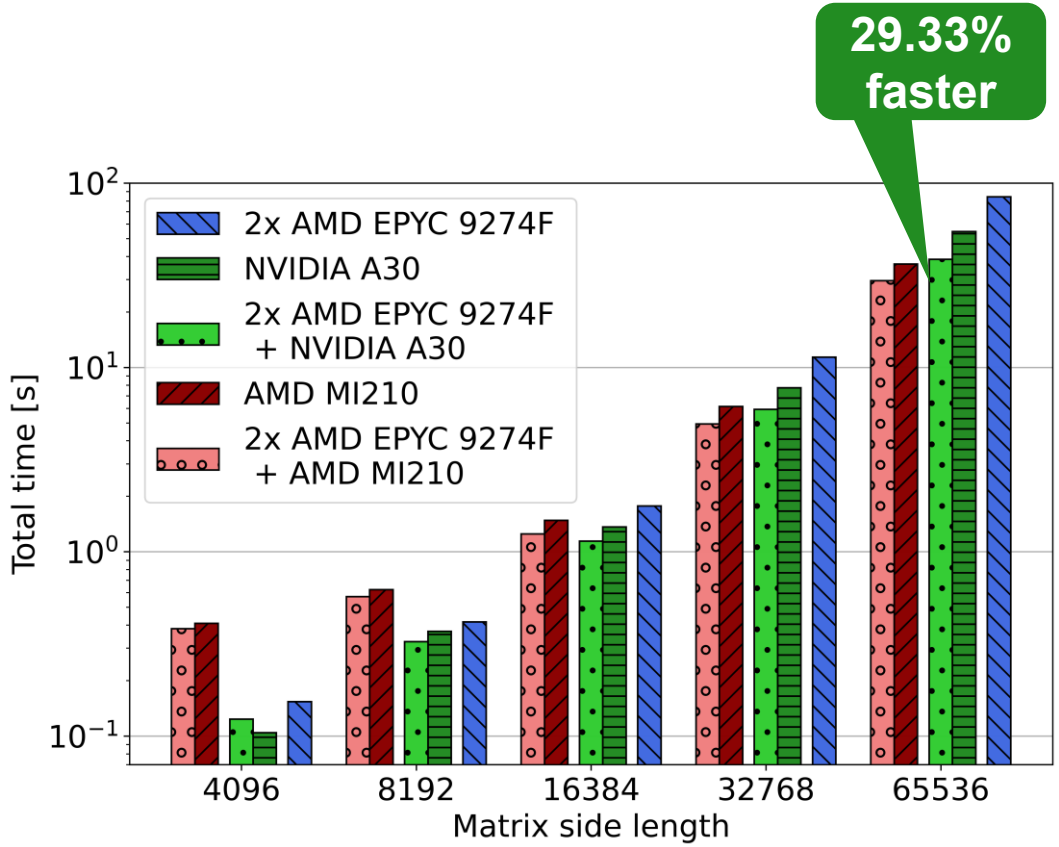

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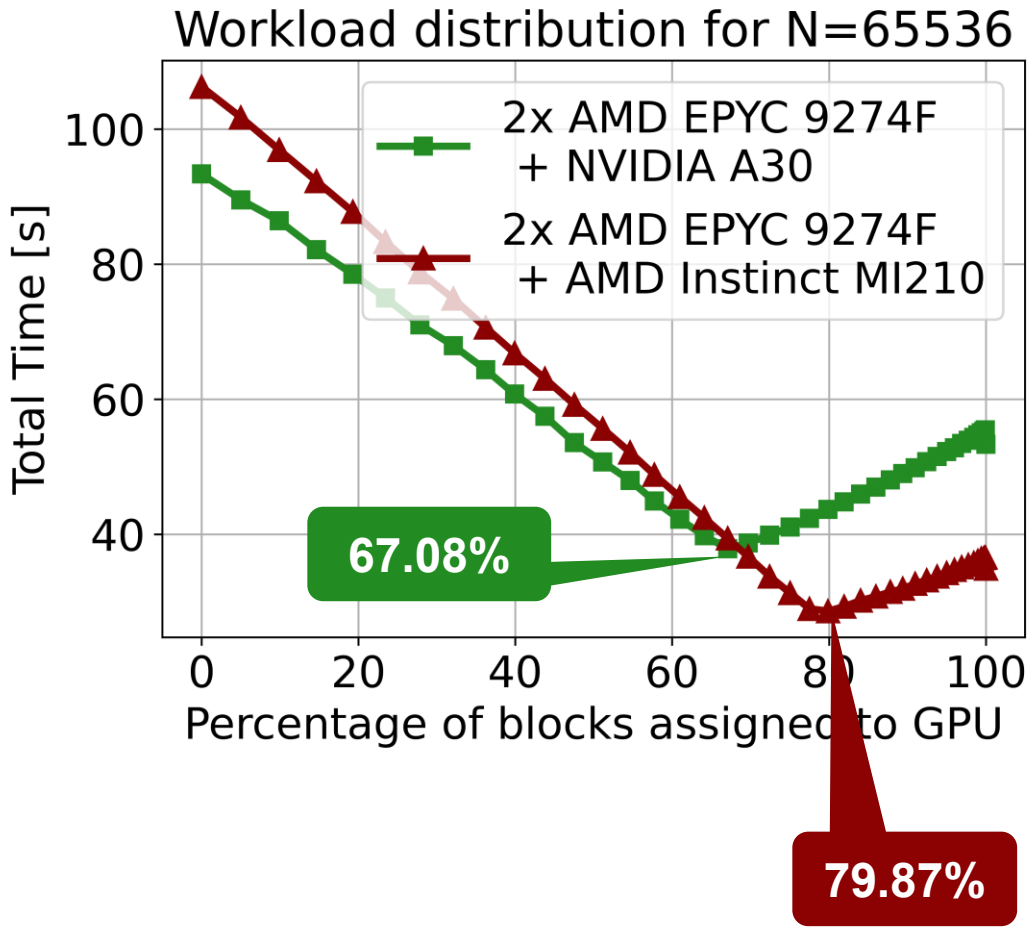

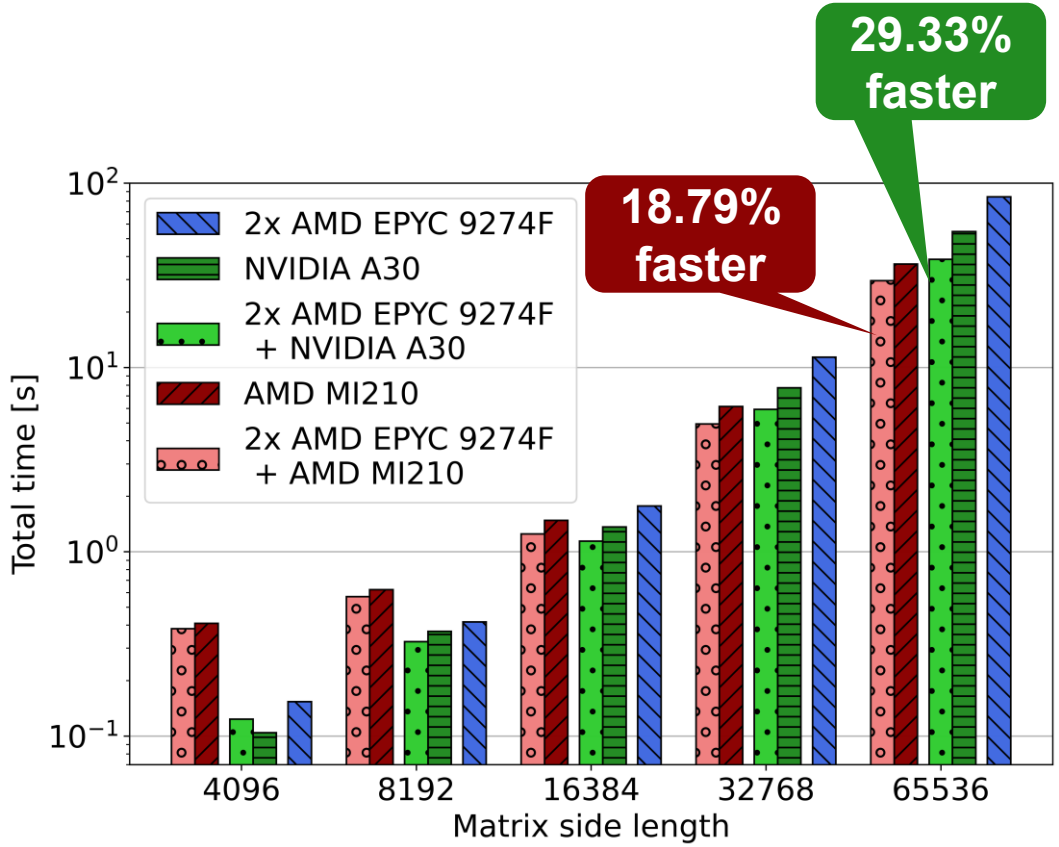

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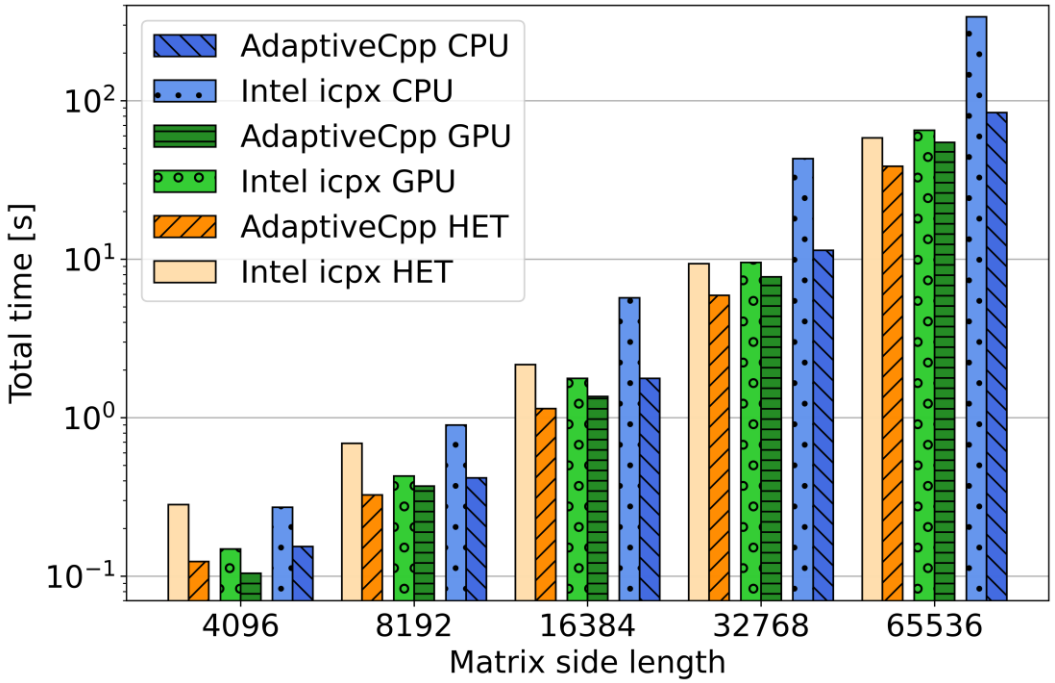

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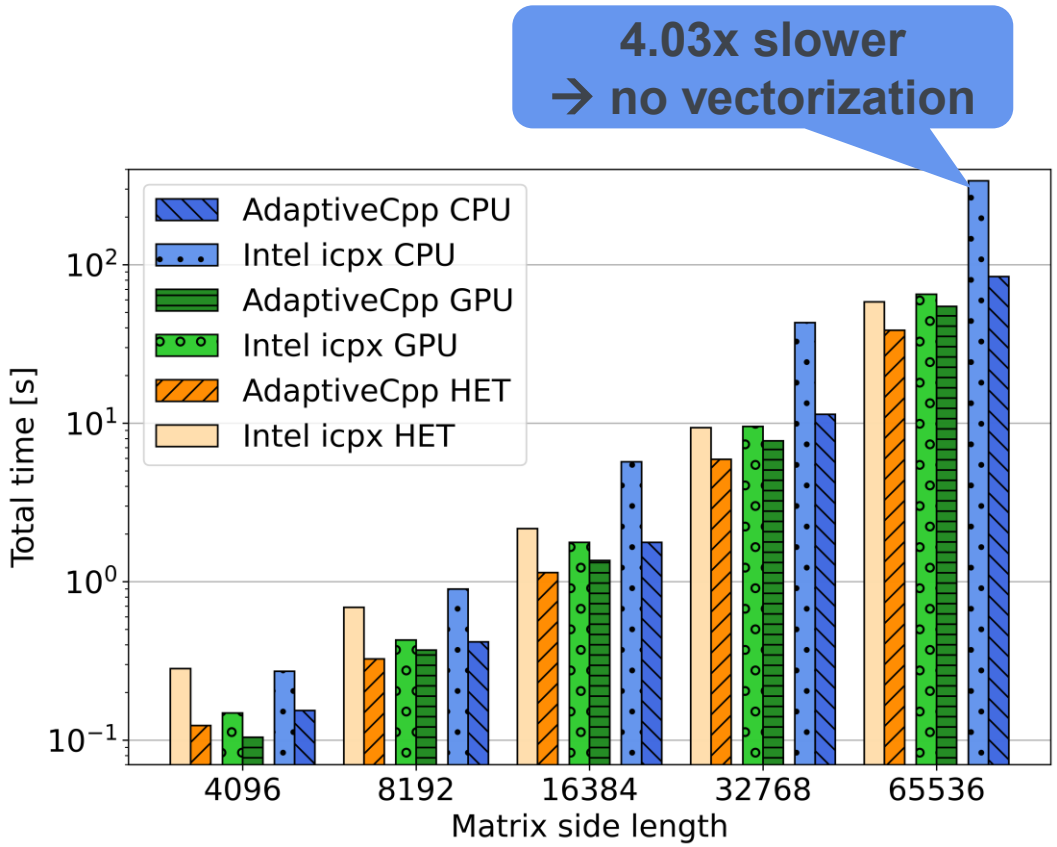

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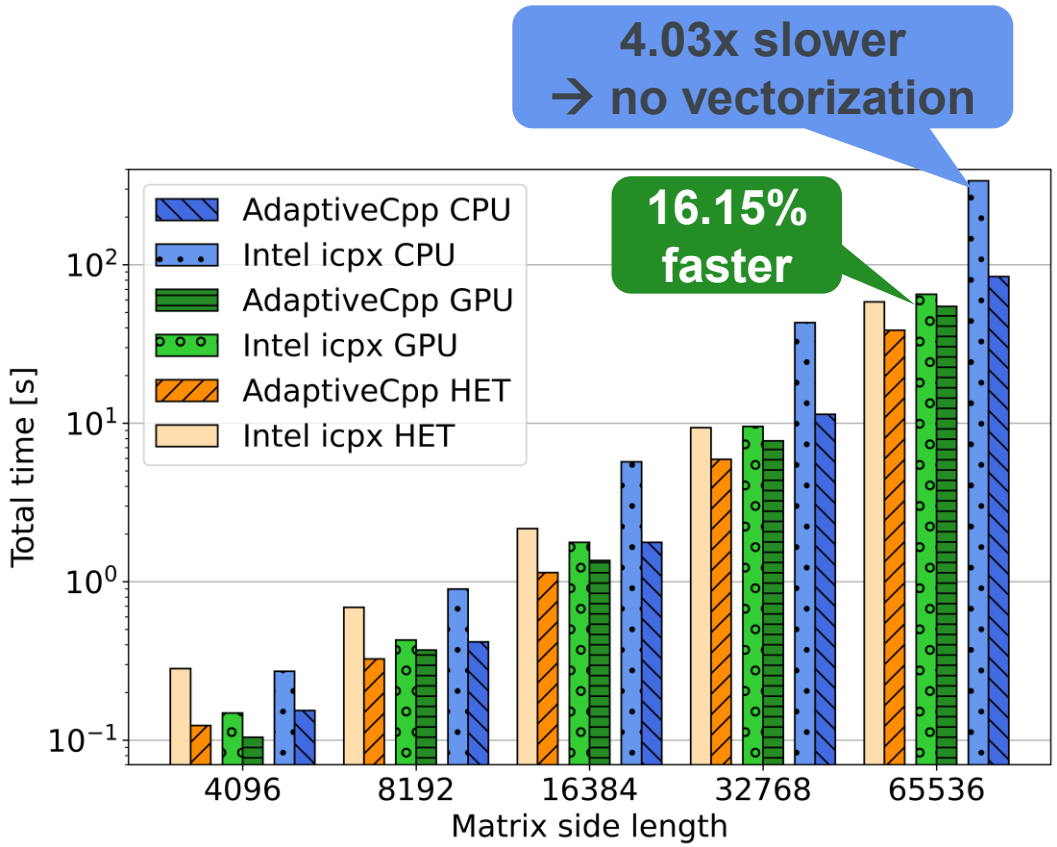

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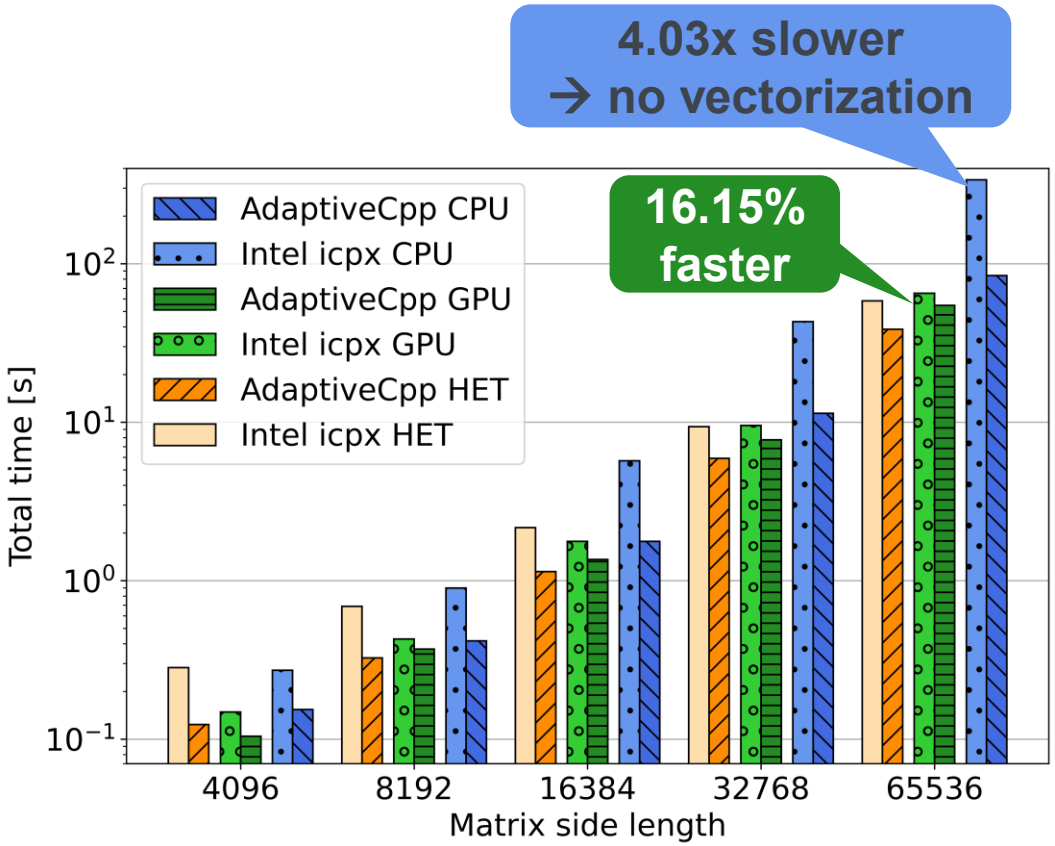

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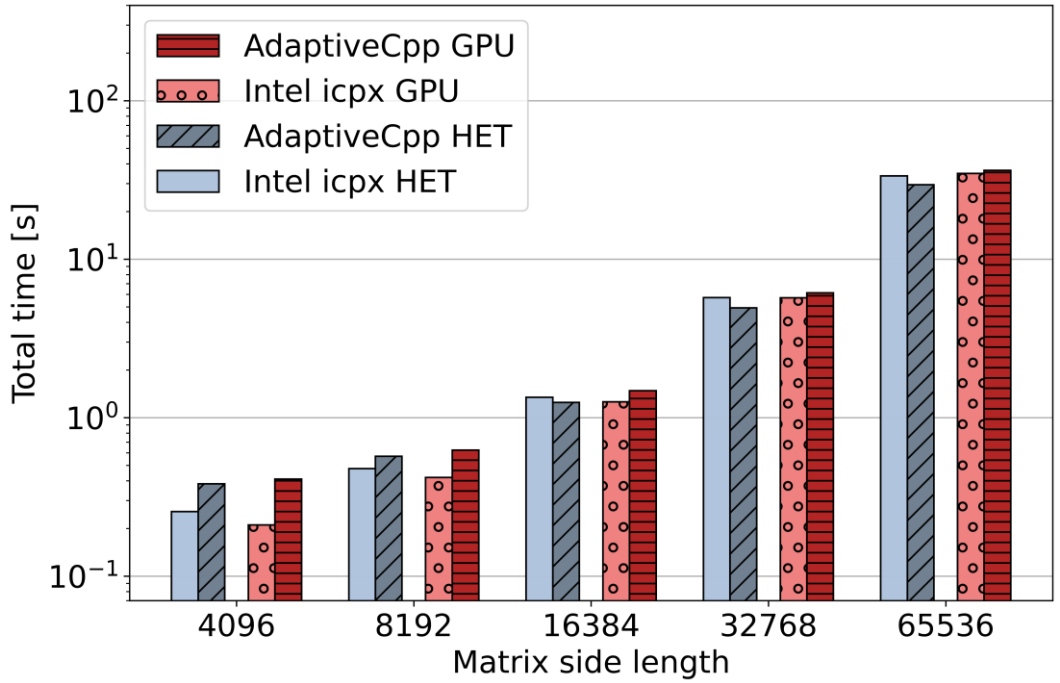

System 2 (AMD MI210)

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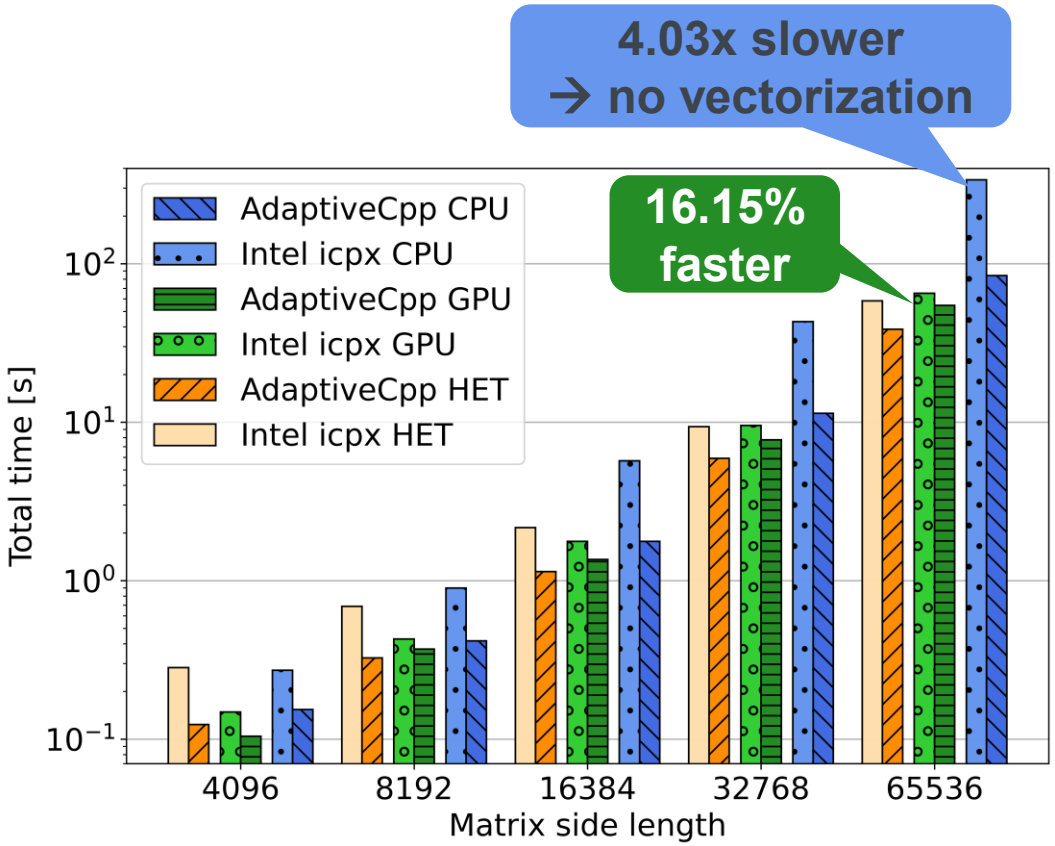

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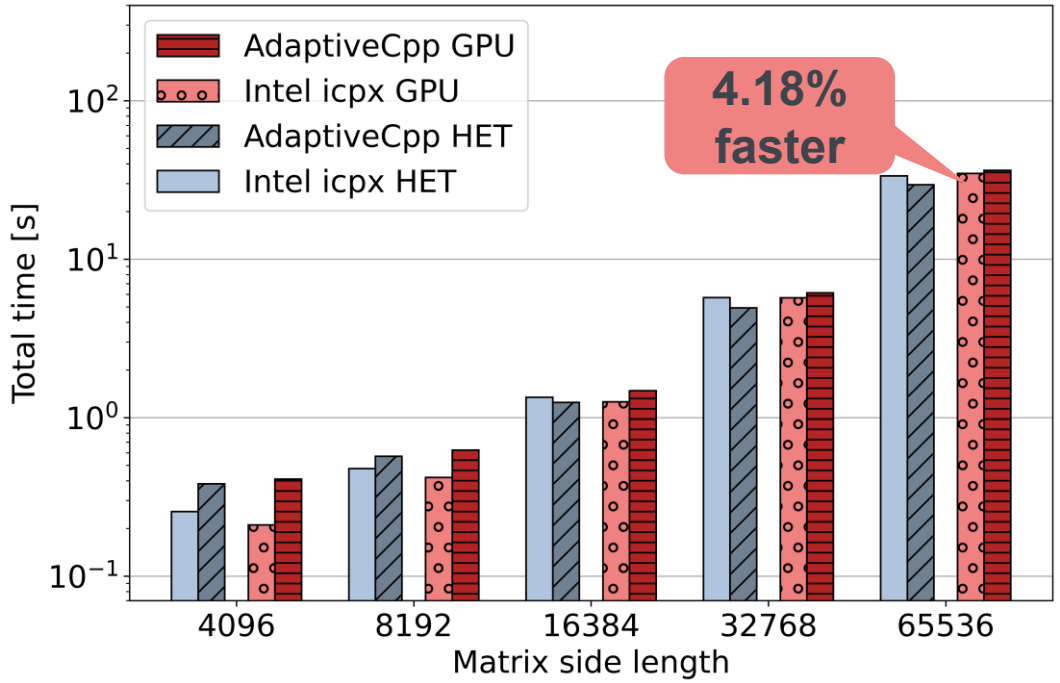

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At least 12% on all four systems

Outlook

Outlook

- Evaluation of the heterogeneous implementations on new compute architectures
  - AMD MI300A APU
  - NVIDIA Grace Hopper Superchip

  → CPU and GPU are tightly coupled
- Analysis of energy consumption

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Thank you!

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