UCLouvain

Fast, Differentiable, GPU-Accelerated Ray Tracing for Multiple Diffraction and Reflection Paths

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Traditional RT
CPU-oriented
Non-differentiable

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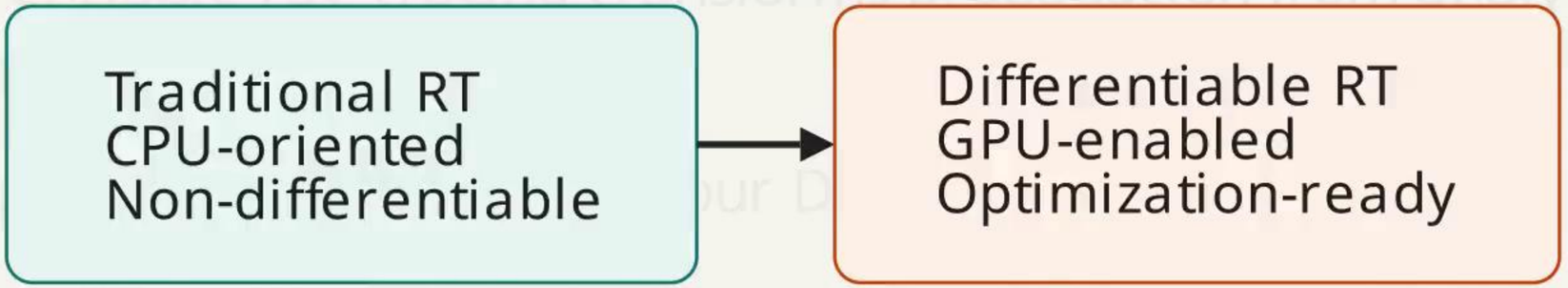

Talk Roadmap

1. Motivation
2. State of the Art
3. Current limitations and our approach
4. Results
5. Ongoing and future research

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- Most implementations remain difficult to batch efficiently on GPUs.

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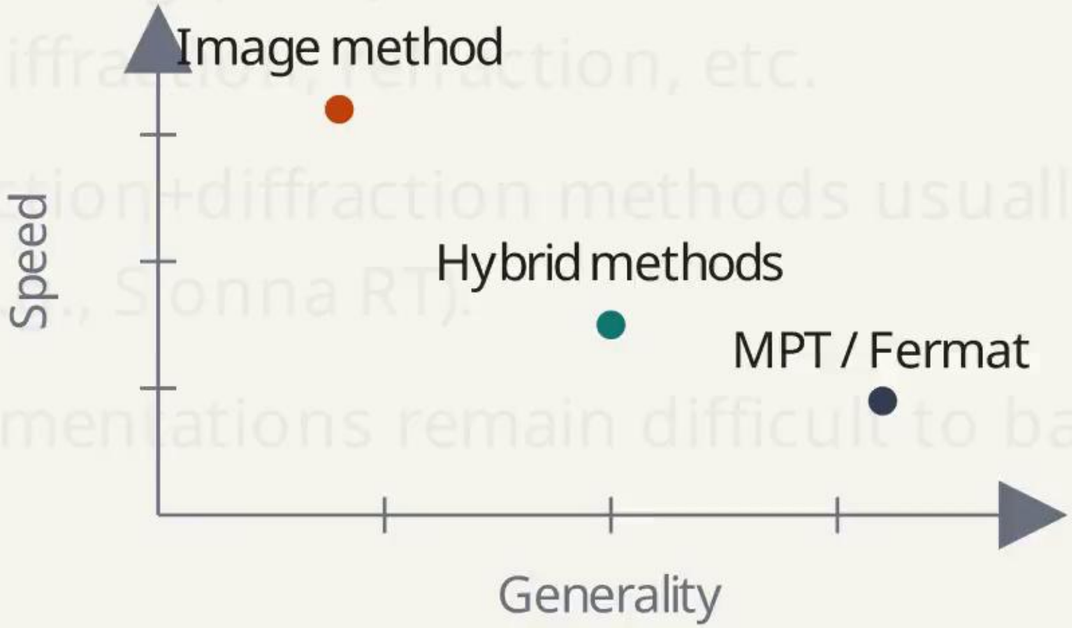

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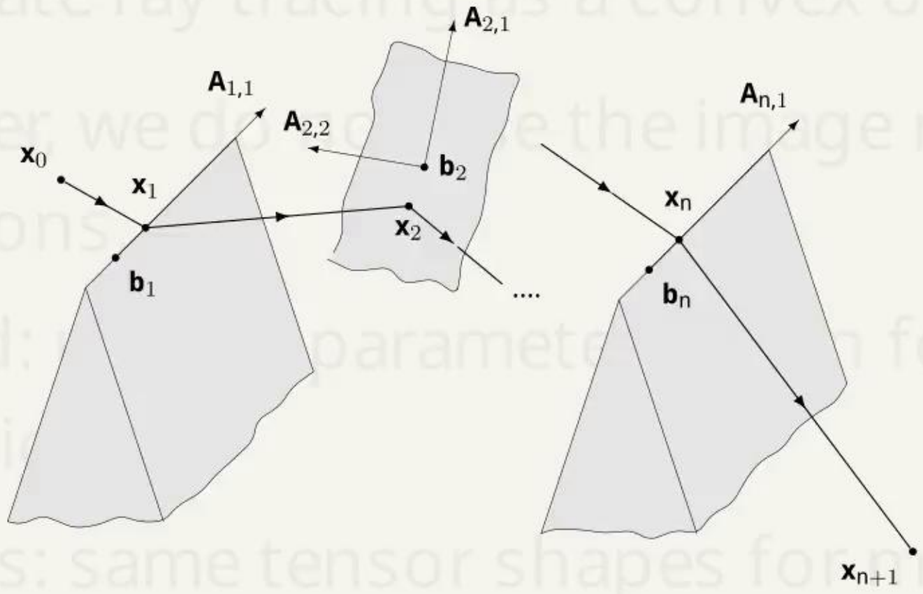

$$\mathbf{T}^* = \arg\min_{\mathbf{T}} L(\mathbf{T}; \mathbf{A}, \mathbf{B})$$

with

$$L(\mathbf{T}; \mathbf{A}, \mathbf{B}) = \sum_i \|\Delta \mathbf{x}_i\|$$

and

$$\mathbf{x}_i = \mathbf{A}_i \mathbf{t}_i + \mathbf{b}_i$$

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$$\min_{\mathbf{T}} \sum_{i} n_i \, \|\Delta \mathbf{x}_i\|$$

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- Run a fixed number of iterations K on GPU to avoid warp divergence and idle threads.

Methodology II: BFGS Solver

Why BFGS over mixed Newton/GD?

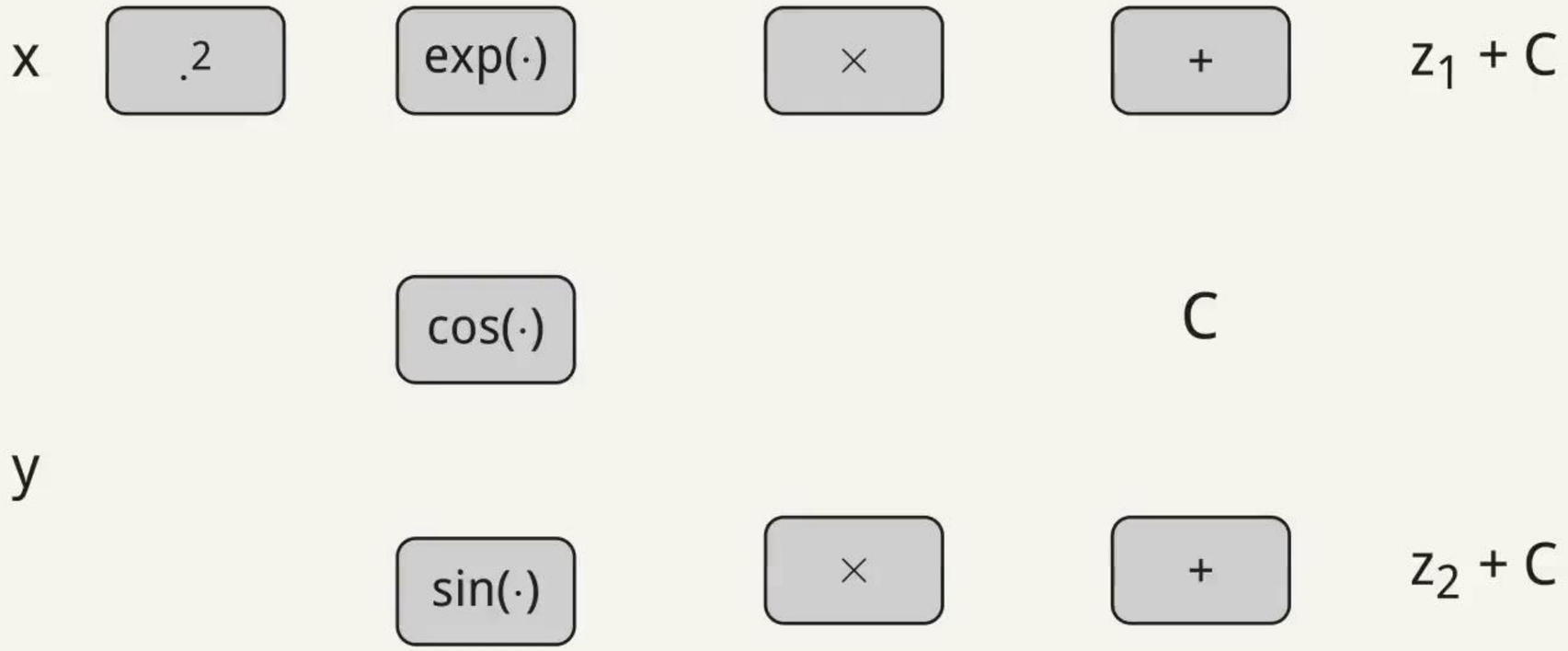
CA's Newton step is sensitive to ill-conditioned Hessians. This appears frequently with zero-padded diffraction dimensions.

BFGS avoids inverting the true Hessian and supports stronger line-search.

$$B_{k+1} = B_k + \frac{y_k y_k^\top}{y_k^\top s_k} - \frac{B_k s_k s_k^\top B_k}{s_k^\top B_k s_k}$$

Methodology III: Reverse-Mode AD

$$f(x, y) = \begin{bmatrix} f_1(x, y) \\ f_2(x, y) \end{bmatrix} = \begin{bmatrix} \cos(y)e^{x^2} + C \\ \sin(y)e^{x^2} + C \end{bmatrix}$$



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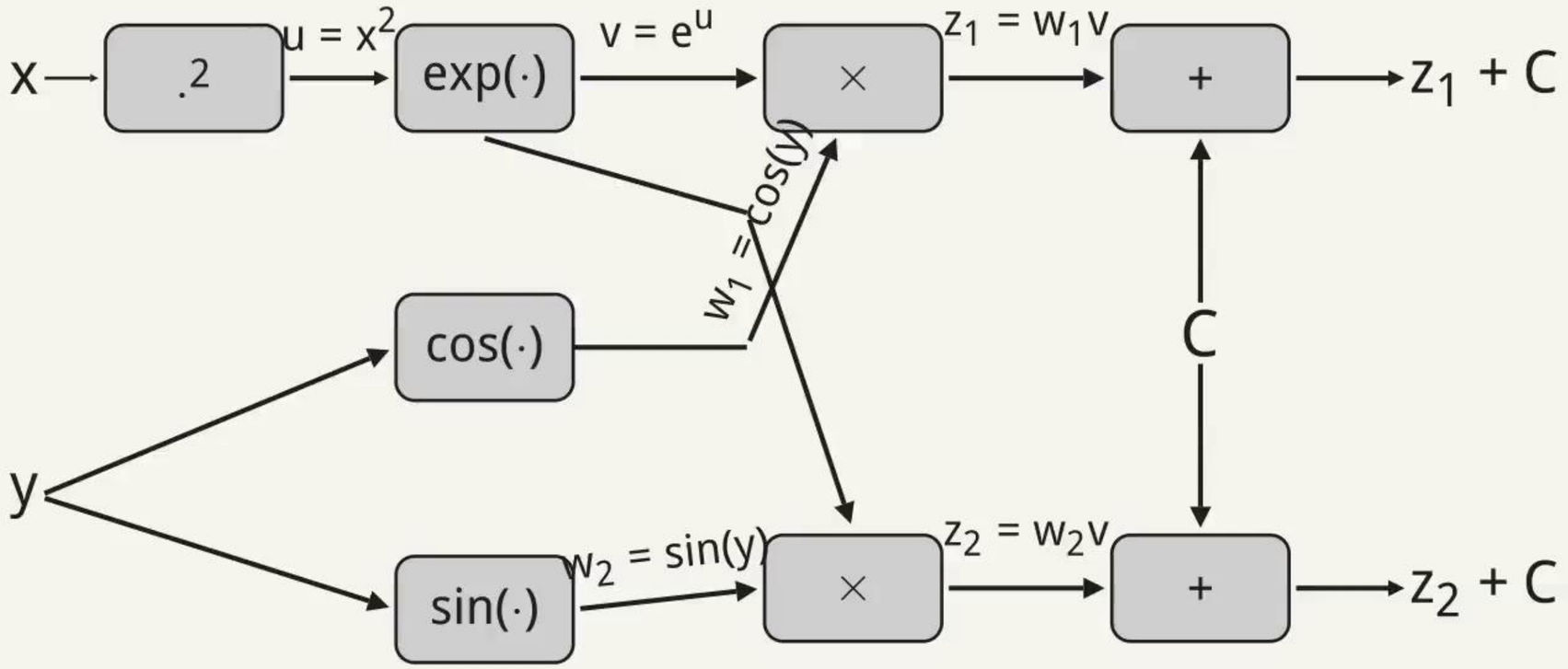

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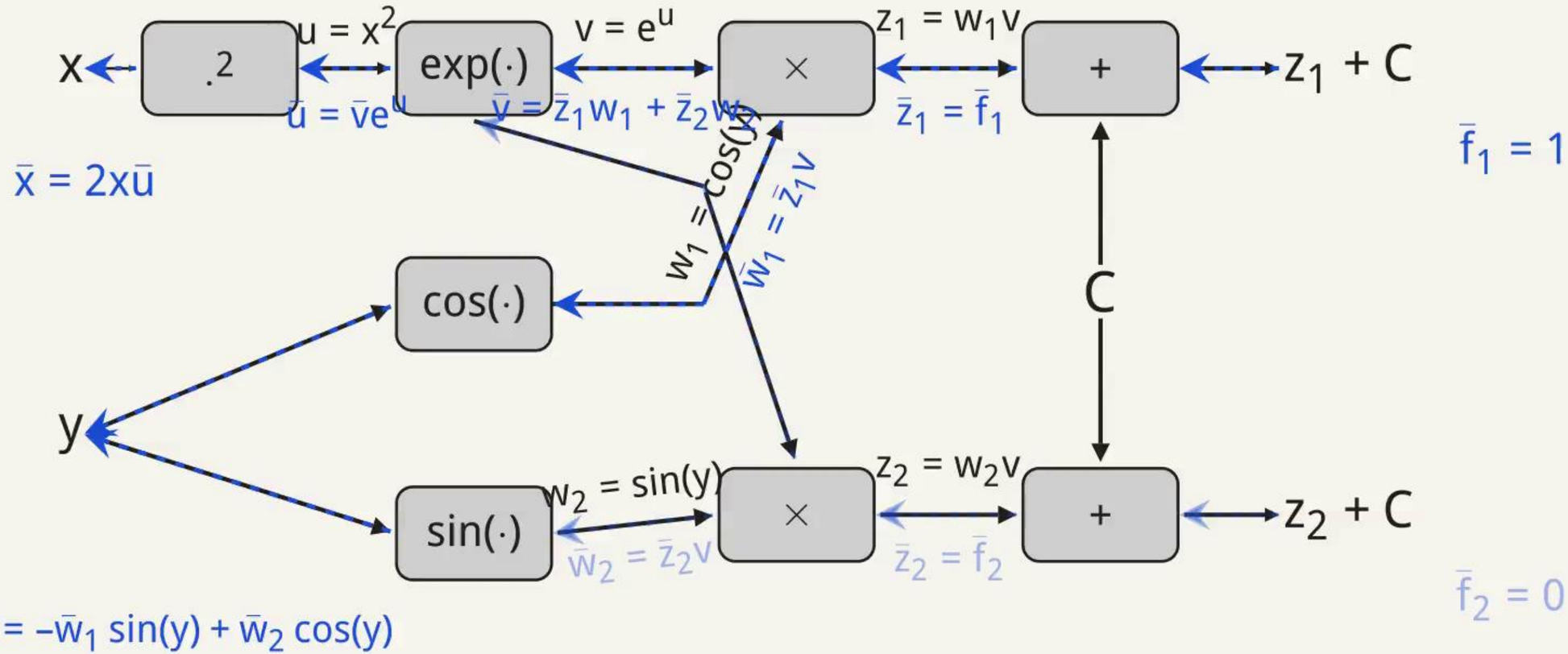

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- Result: gradients without storing all iterative states.

Methodology IV: Implicit Differentiation

Unrolled iterative reverse-mode

memory $\propto K$

backward time $\propto K$

$$\nabla_{\mathbf{T}} L(\mathbf{T}^*; \theta) = \mathbf{0}$$

$$\frac{\partial \mathbf{T}^*}{\partial \theta} = -H^{-1} \frac{\partial}{\partial \theta} \nabla_{\mathbf{T}} L$$

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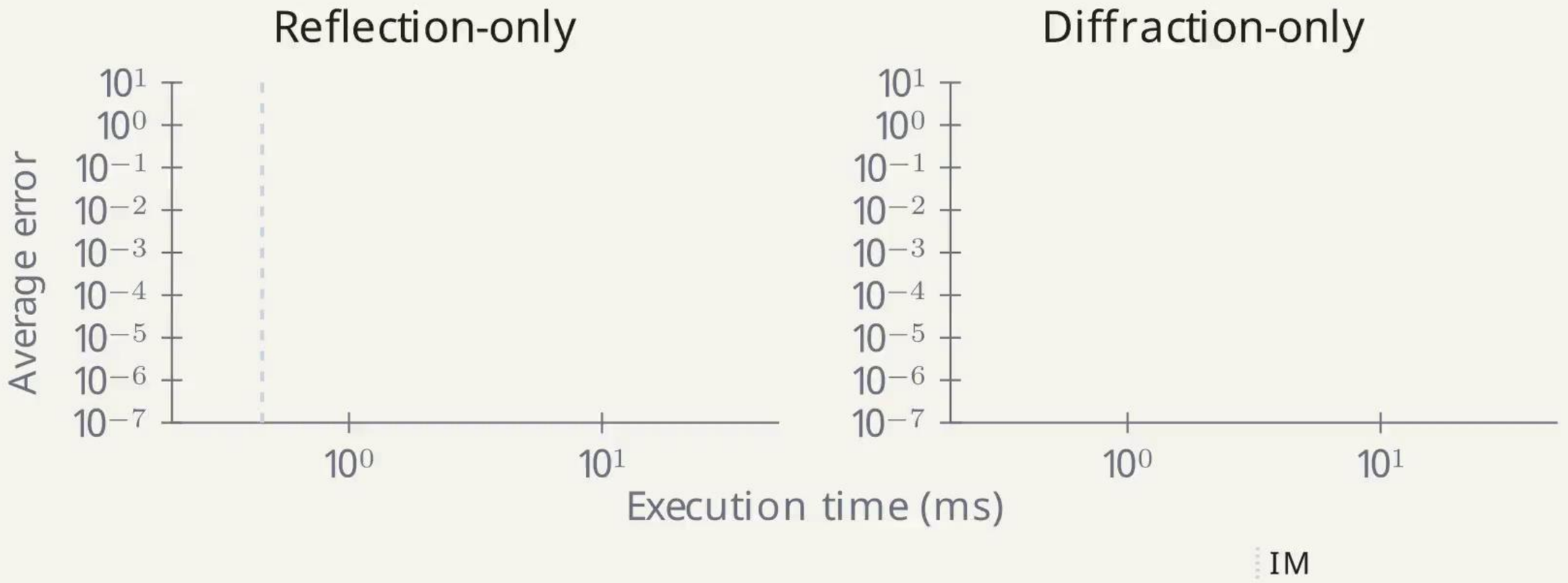
- Metrics: runtime and average interaction-point error.

Results: Accuracy vs Runtime



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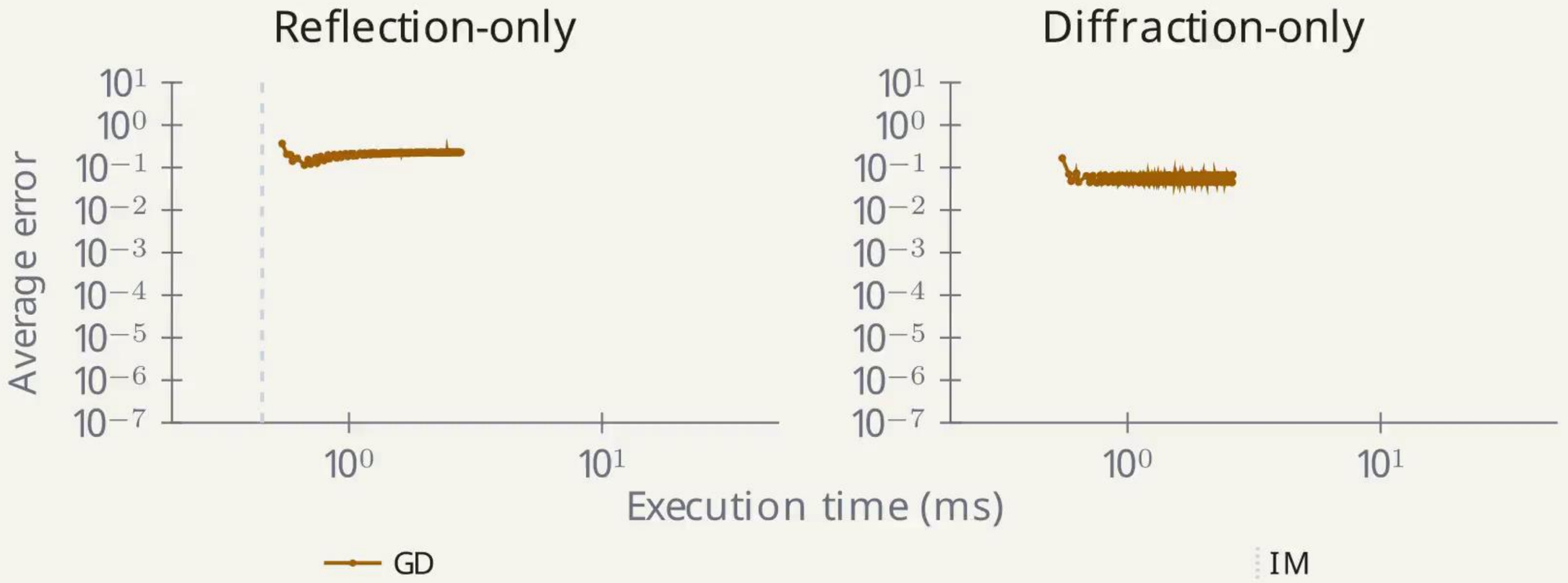

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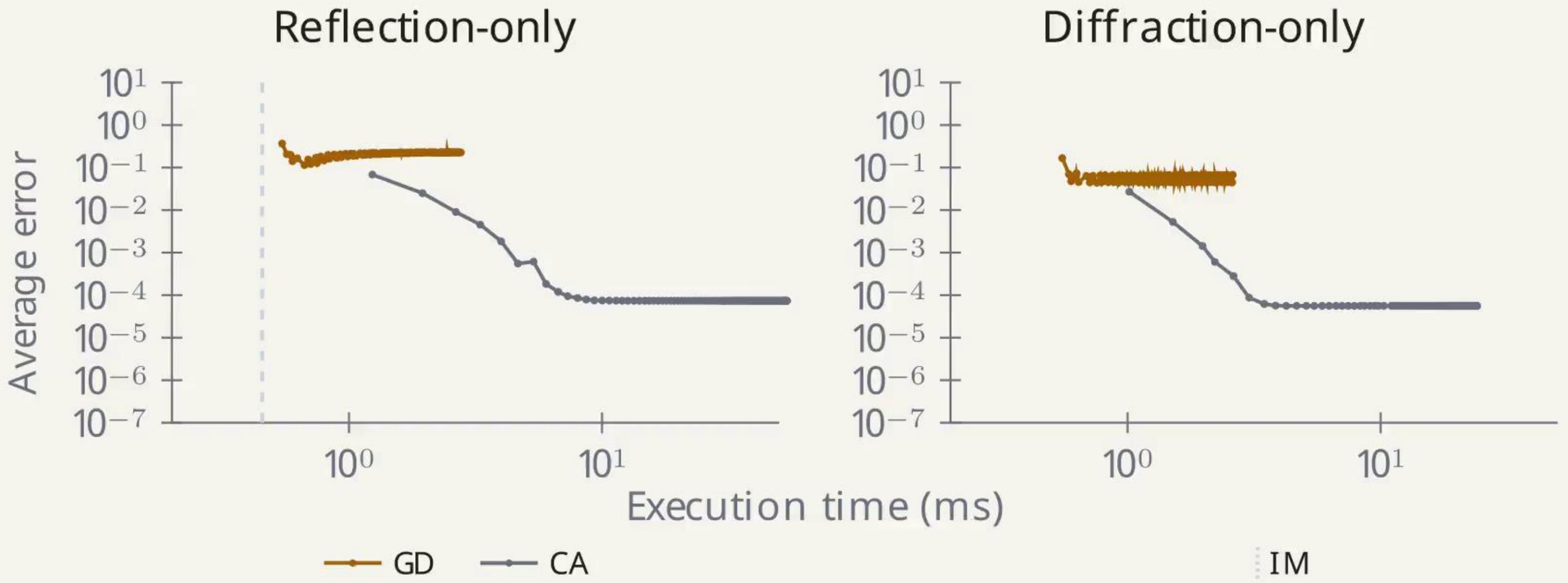

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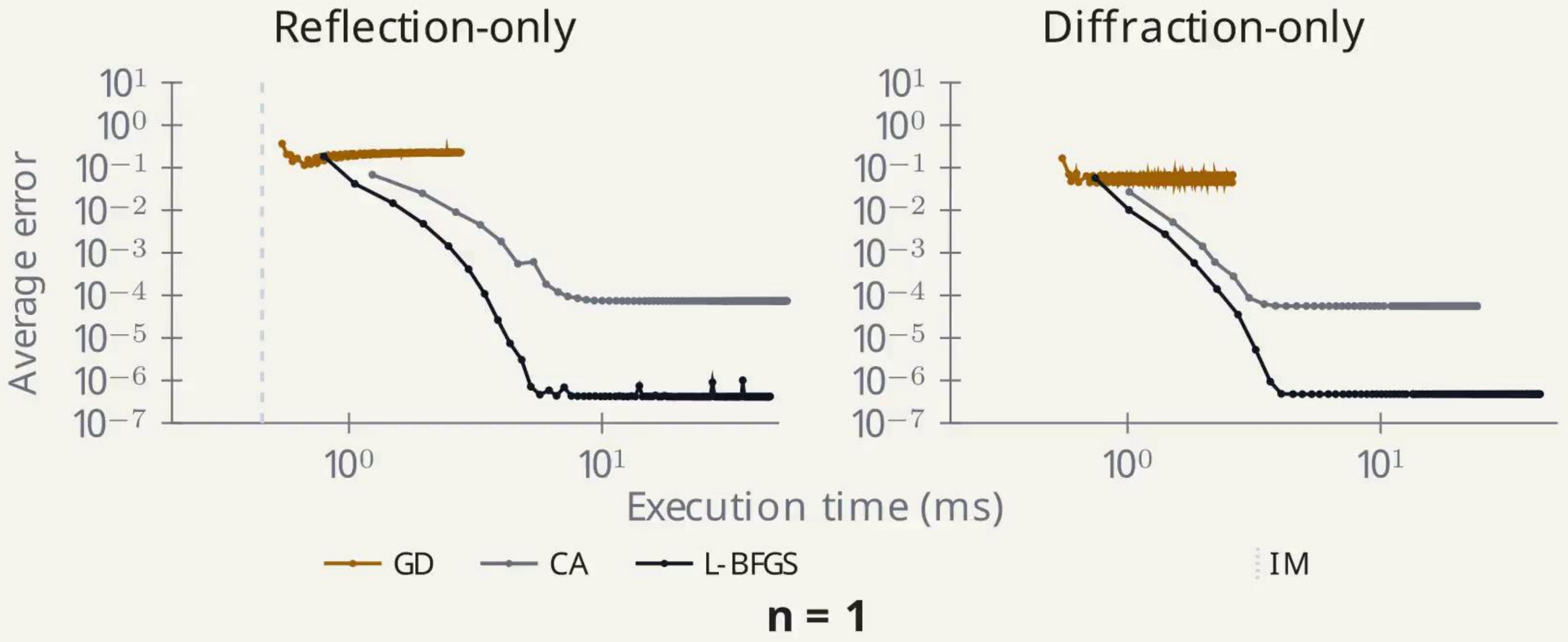

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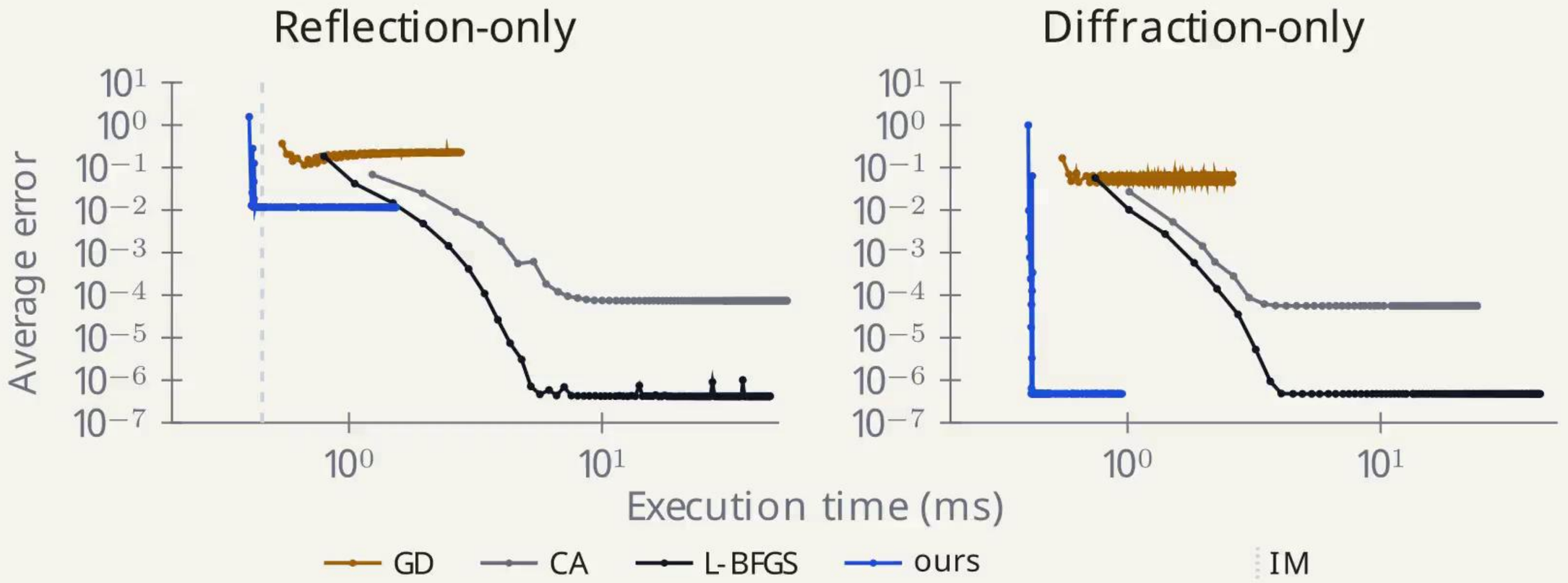

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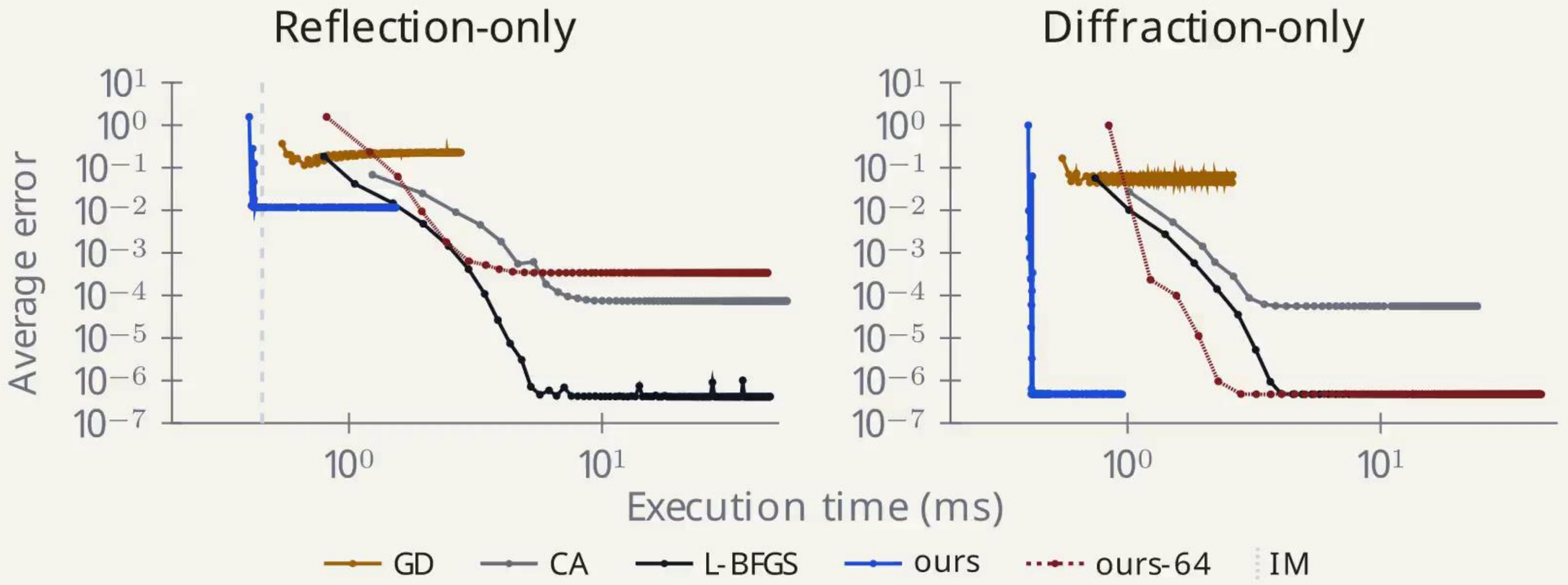

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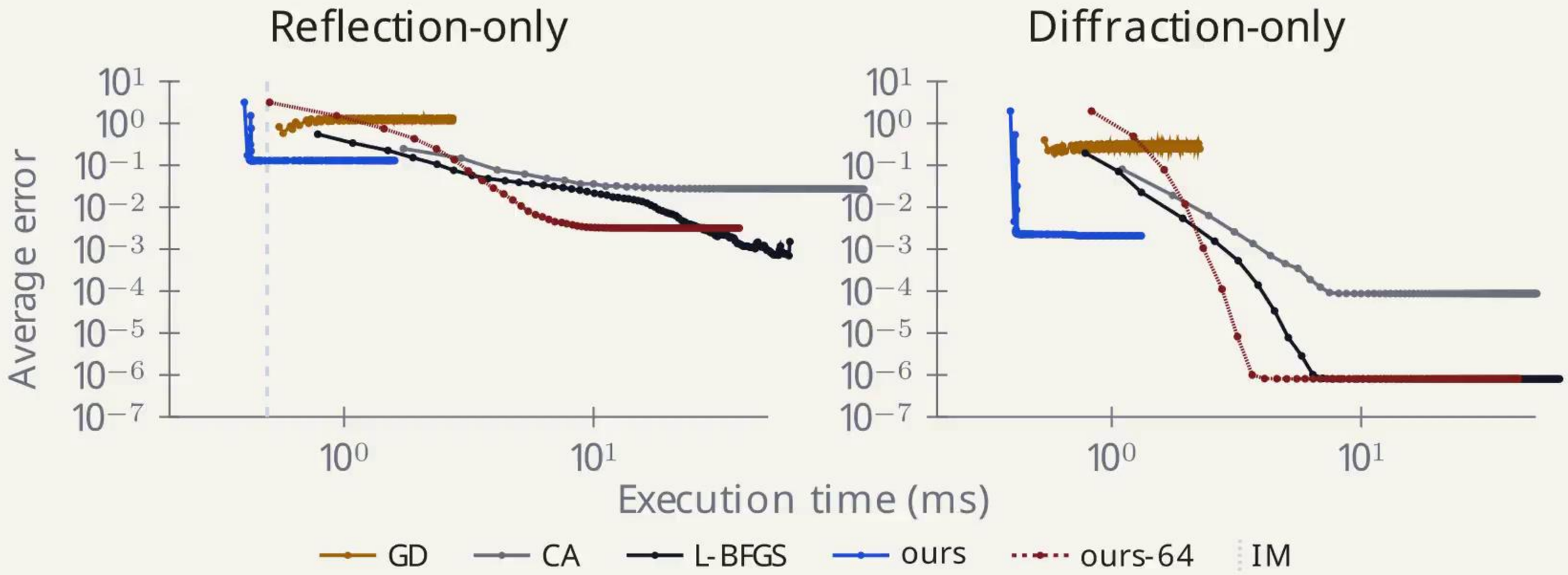

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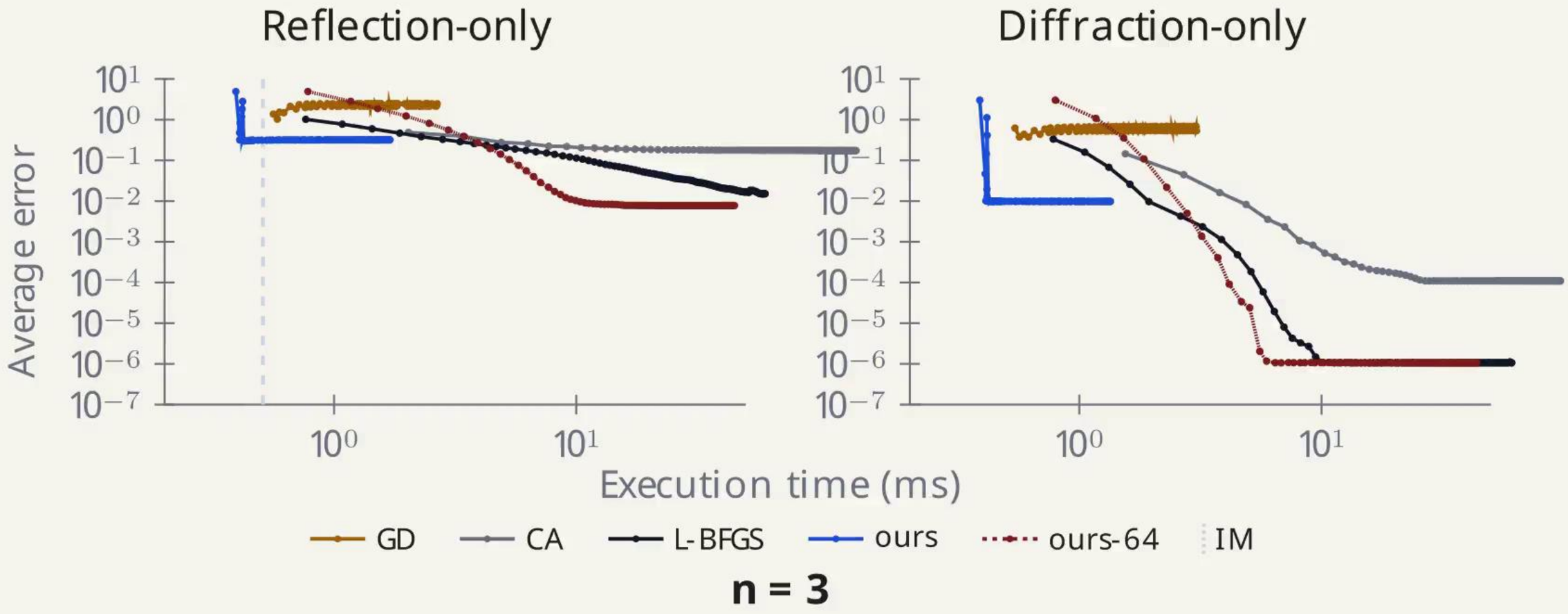

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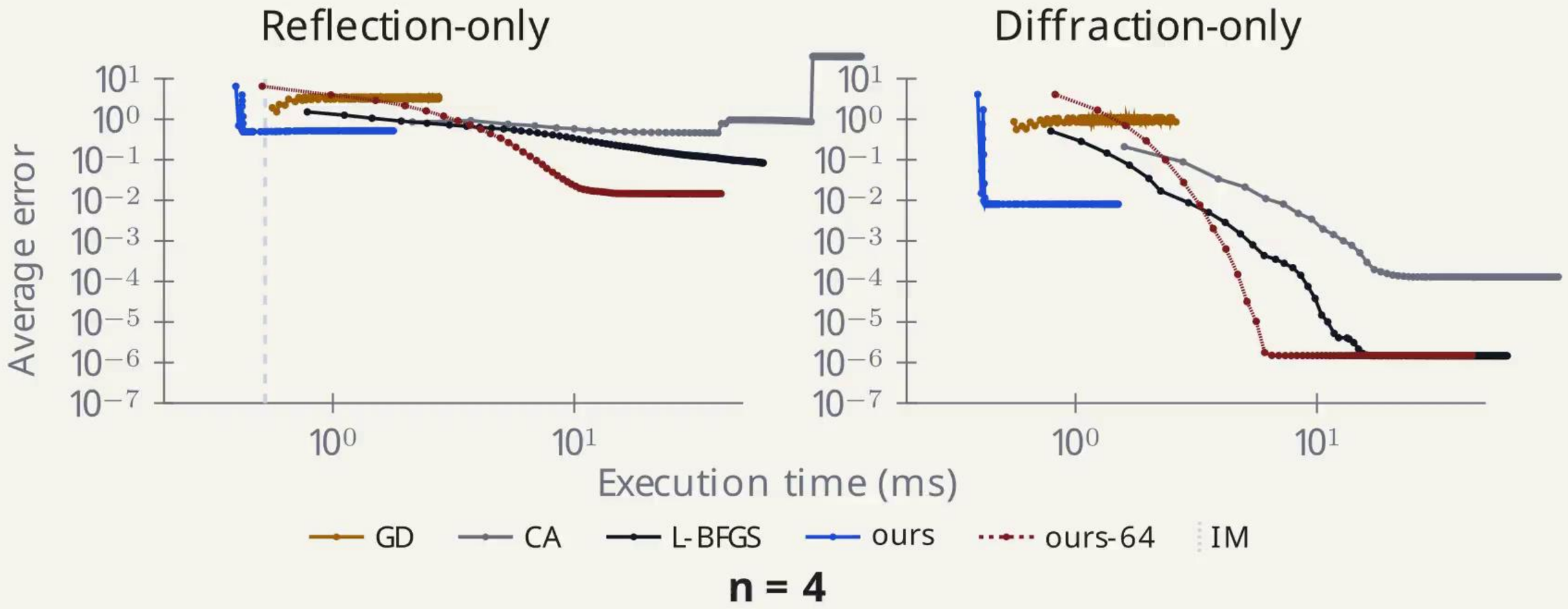

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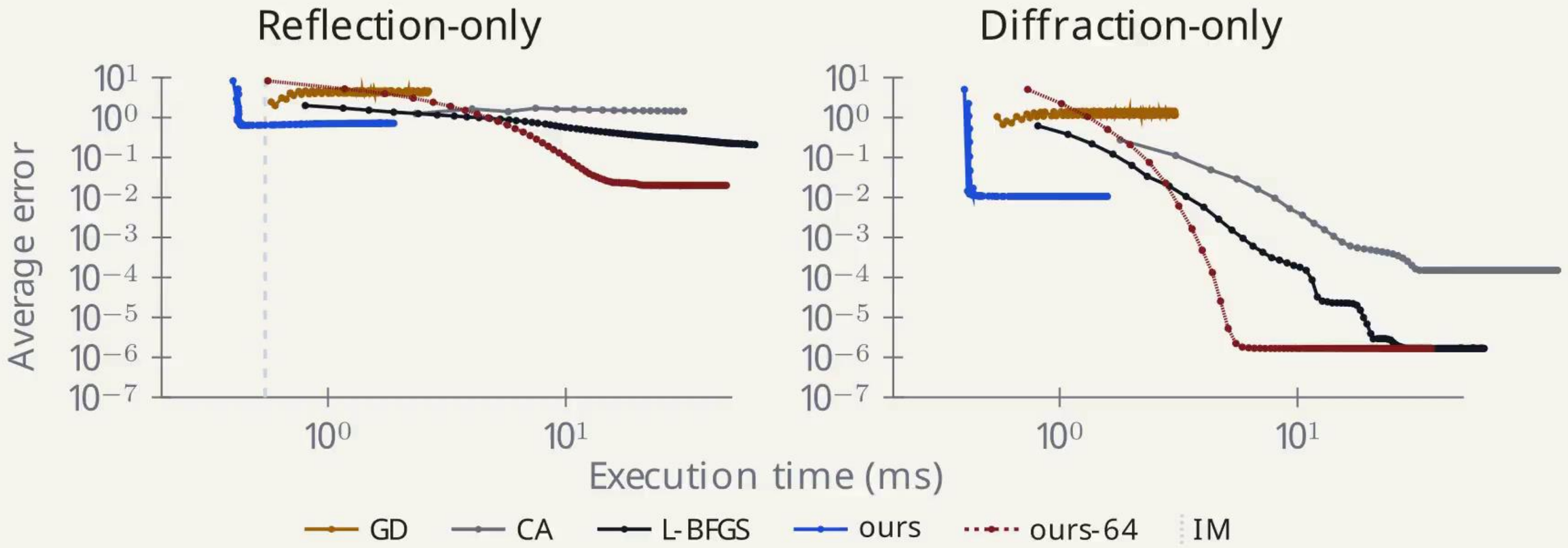

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Better solvers exist in theory; practical open GPU implementations remain the bottleneck.

Thank you

Happy to answer questions!

DiffeRT

GitHub Implementation

Presentation with Manim Slides, an open-source tool