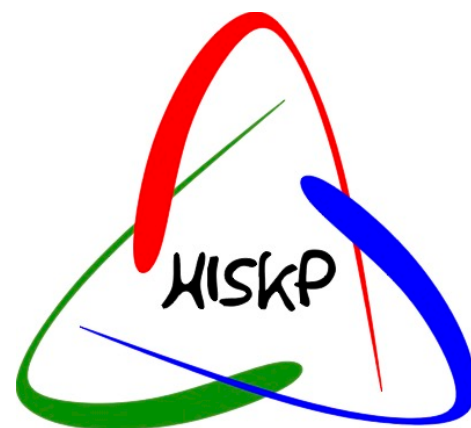


Toward Efficient Trotter-Suzuki Schemes for Long-Time Quantum Dynamics

Marko Maležič, Johann Ostmeyer

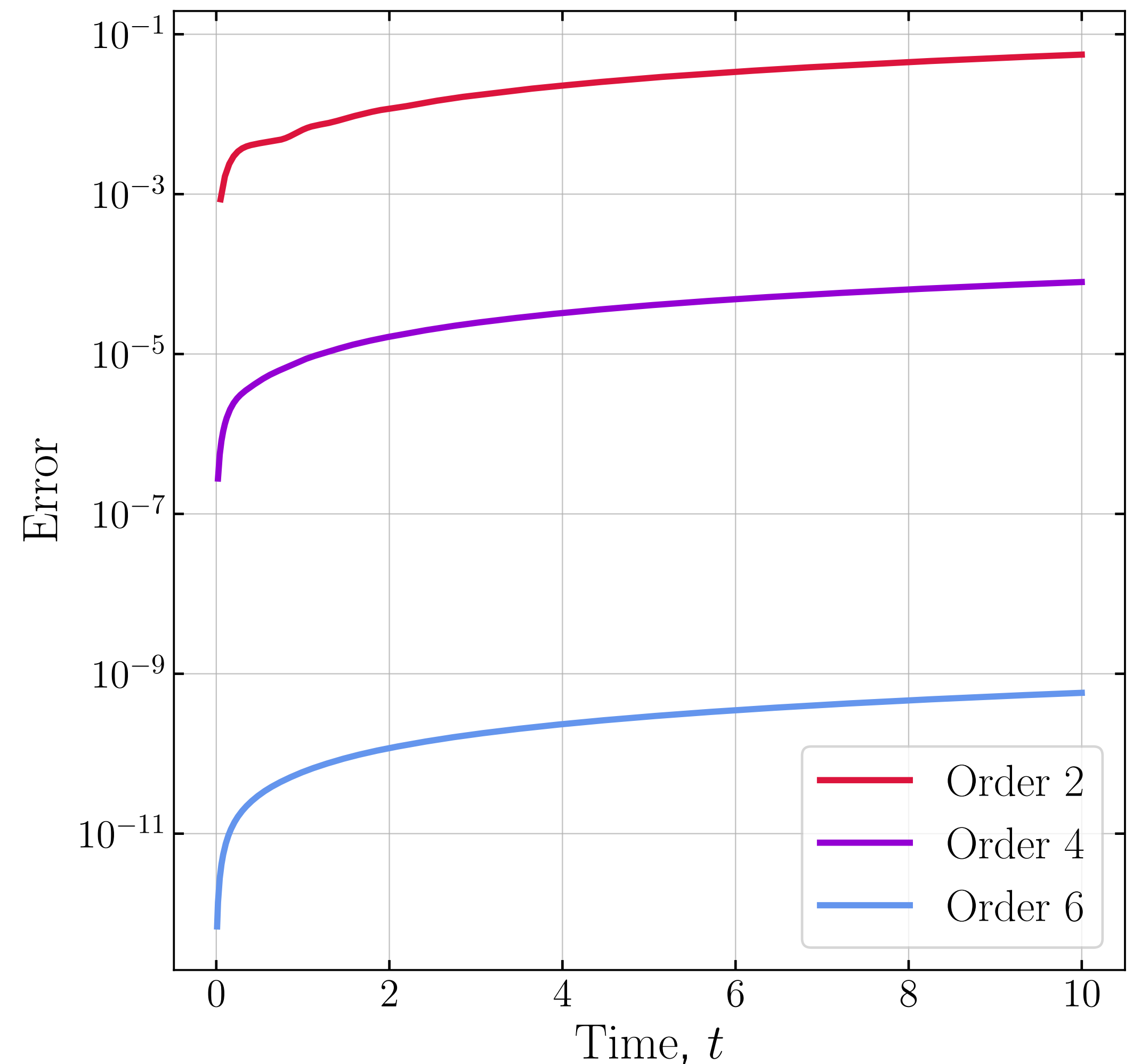


3.9.2025

Trento ECT*, Hamiltonian LGT workshop

Motivation

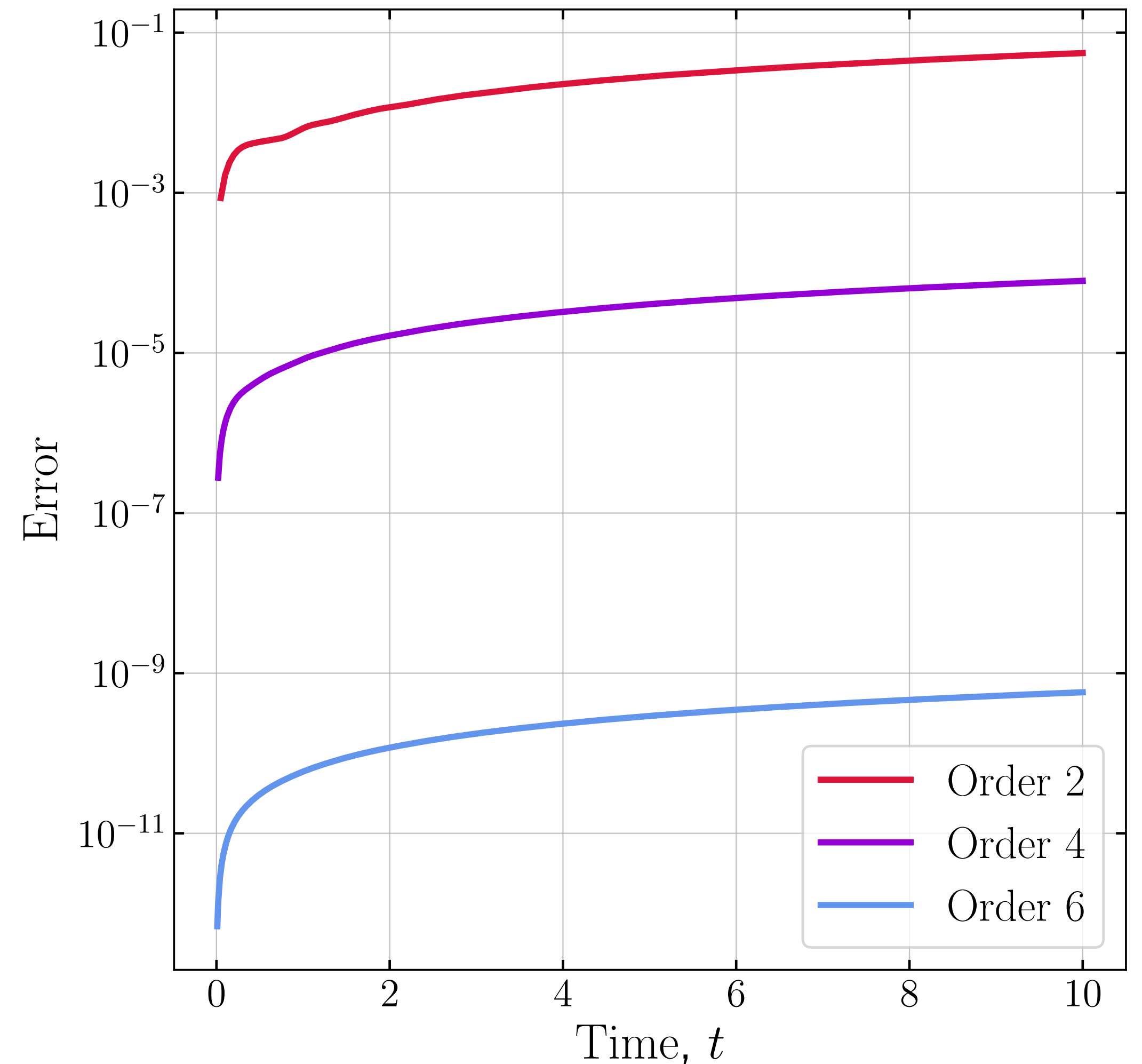
- Accurate long-time quantum simulations are challenging in complex systems
- Limits on access to observables and ground state properties
- Accumulation of errors in time both on classical and quantum hardware



Motivation

- Quantum computers also face hardware problems, e.g. Decoherence and gate depth
- Improving theoretical methods could reduce simulation error
- Time evolution operator:

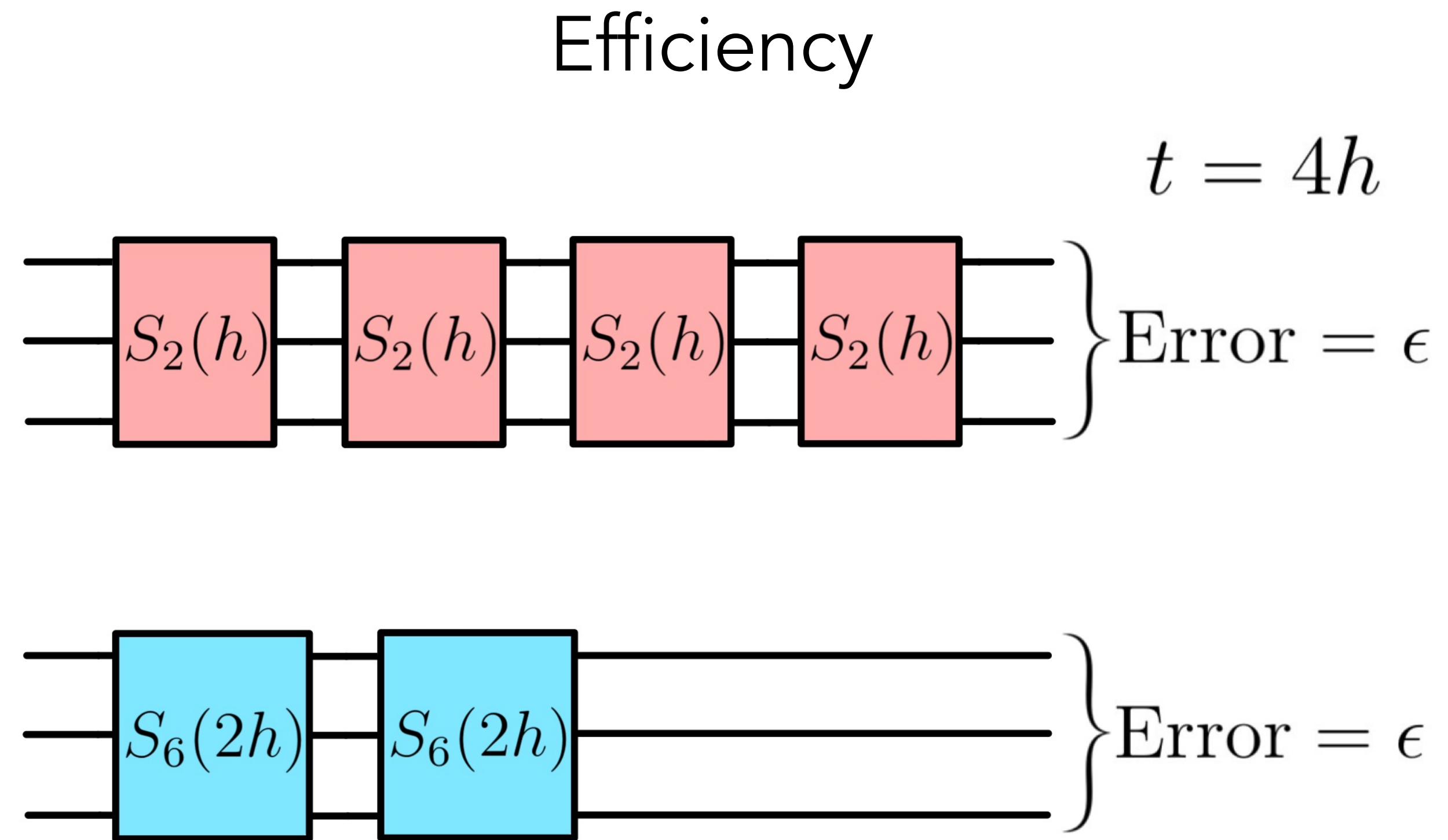
$$U(t) = e^{-iHt} \approx [S_n(h)]^{t/h}$$



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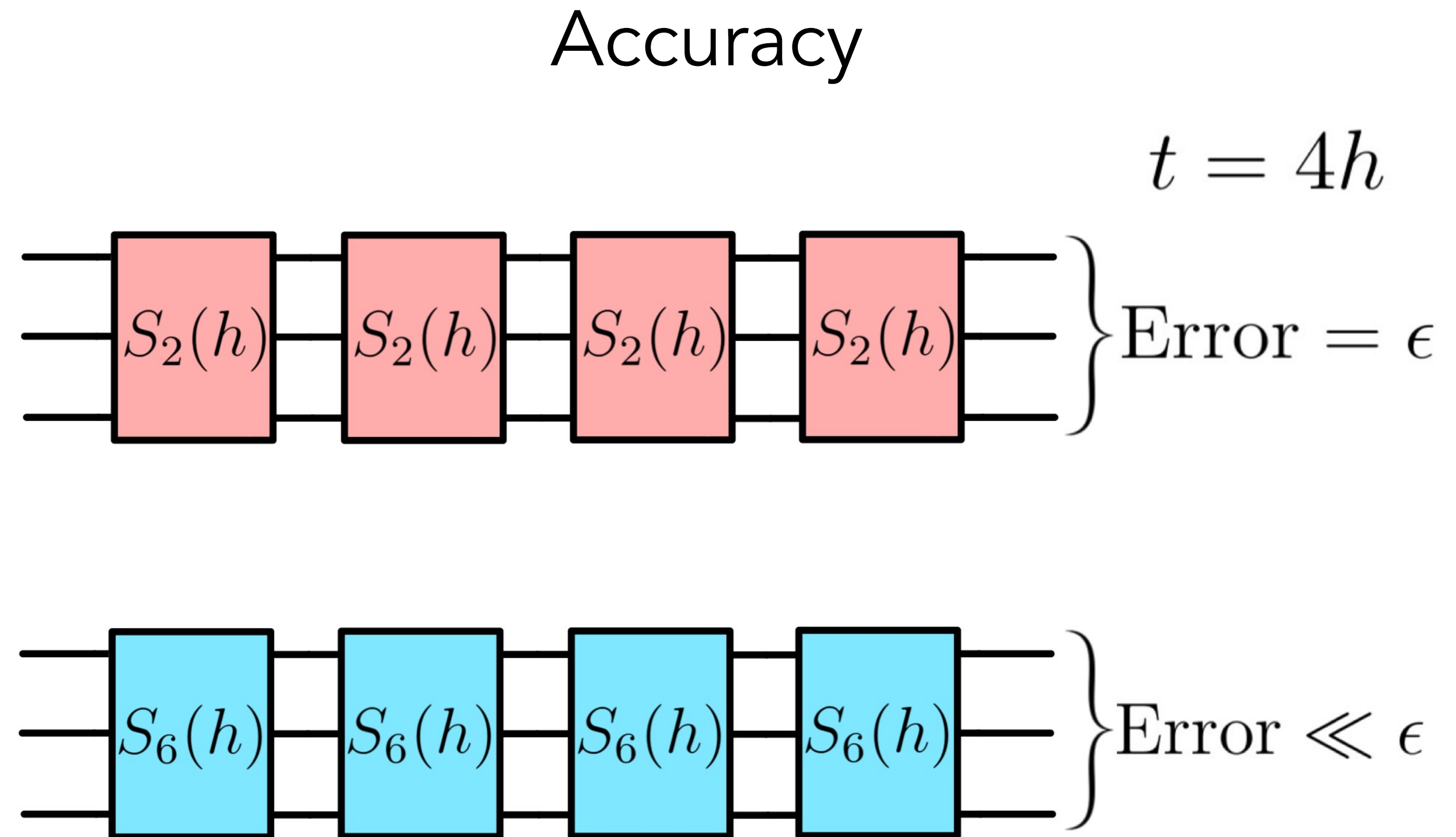
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- Time evolution operator:

$$U(t) = e^{-iHt} \approx [S_n(h)]^{t/h}$$



Trotter-Suzuki decompositions

Time evolution

- Schrödinger equation: $i\frac{\partial}{\partial t}|\psi(t)\rangle = H|\psi(t)\rangle$
- Solved by the time evolution operator $U(t) = e^{-iHt} : |\psi(t)\rangle = U(t)|\psi(0)\rangle$
- Imaginary time evolution ($t = -i\tau$) : $|\psi(0)\rangle = \lim_{\tau \rightarrow \infty} e^{-H\tau}|\psi(0)\rangle$

Trotter-Suzuki decompositions

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- Imaginary time evolution ($t = -i\tau$) : $|\psi(0)\rangle = \lim_{\tau \rightarrow \infty} e^{-H\tau}|\psi(0)\rangle$
- Analytical solutions possible for simple, small and symmetric systems
- Exact diagonalization possible for small systems (e.g. spin chains with $L \lesssim 20$)
- Exchange scalability for a discretization error using Trotterizations

$$U(t) \approx [S_n(h)]^{t/h}$$

Trotter-Suzuki decompositions

Baker-Campbell-Hausdorf formula

- Hamiltonian with two terms: $H = A + B$
- BCH formula: $e^{Ah}e^{Bh} = e^{(A+B)h + \frac{h^2}{2}[A,B] - \frac{h^3}{24}[A,[A,B]] + \frac{h^3}{12}[B,[B,A]] + \mathcal{O}(h^4)}$

Trotter-Suzuki decompositions

Baker-Campbell-Hausdorff formula

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- Non-commuting case: $e^{Ah}e^{Bh} = e^{(A+B)h + \mathcal{O}(h^2)}$ - Order $n = 1$
- Leapfrog (Verlet) scheme: $e^{\frac{A}{2}h}e^{Bh}e^{\frac{A}{2}h} = e^{(A+B)h + \mathcal{O}(h^3)}$ - Order $n = 2$
- Symmetric schemes lead to even orders without much cost

Trotter-Suzuki decompositions

Scheme construction

- Construction of higher order decompositions ($n \geq 4$)
- Suzuki and Yoshida methods - Construction using lower order schemes
- Both methods fail to find maximally efficient schemes

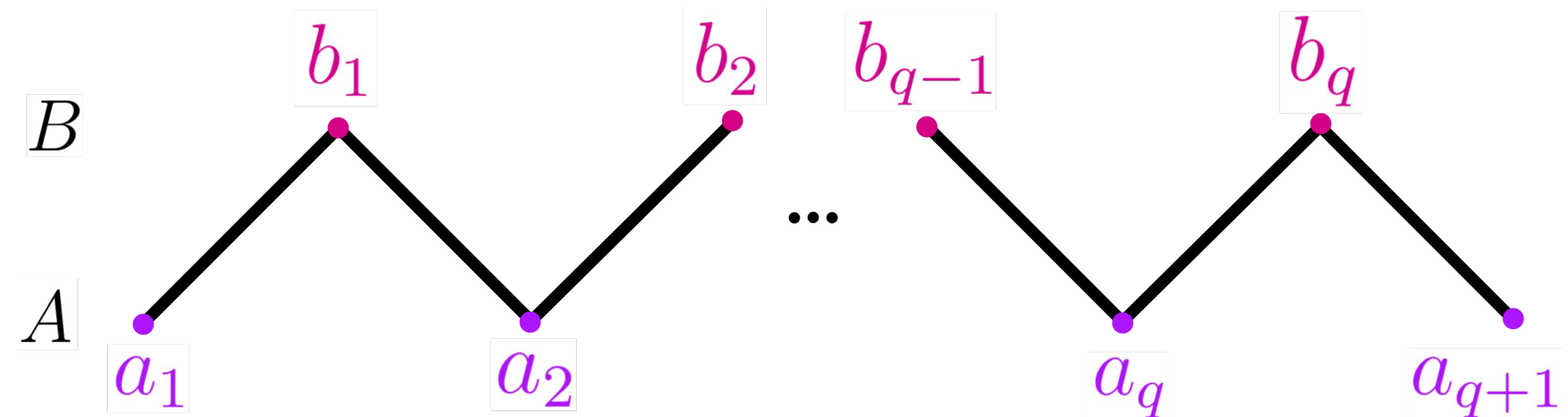
Trotter-Suzuki decompositions

Scheme construction

- Construction of higher order decompositions ($n \geq 4$)
- Omelyan's method - Construction from scratch
- Assume symmetric (not necessarily real) parameters ($a_1 = a_{q+1}$, $b_1 = b_q$)

$$e^{(A+B)h+O_1h+O_3h^3+O_5h^5} = e^{a_1Ah}e^{b_1Bh} \dots e^{b_qBh}e^{a_{q+1}Ah}$$

- Notation: - Stage, $e^{a_iA_ih}$
 - Ramp (up, down)
 - No. cycles q



Trotter-Suzuki decompositions

Omelyan's method

- Assume symmetric (not necessarily real) parameters ($a_1 = a_{q+1}$, $b_1 = b_q$)

$$e^{(A+B)h+O_1h+O_3h^3+O_5h^5} = e^{a_1Ah} e^{b_1Bh} \dots e^{b_qBh} e^{a_{q+1}Ah}$$

- Valid if, $\nu = \sigma = 1$ which is guaranteed by:

$$\sum_i a_i = \sum_i b_i = 1$$

$$O_1 = (\nu - 1)A + (\sigma - 1)B,$$

$$O_3 = \alpha C_1 + \beta C_2, \quad C_1 = [A, [A, B]], \quad C_2 = [B, [B, A]],$$

$$O_5 = \sum_{k=1}^6 \gamma_k D_k, \quad D_1 = [A, [A, [A, [A, B]]]], \quad D_2 = [A, [A, [B, [A, B]]]],$$

$$D_3 = [B, [A, [A, [A, B]]]], \quad D_4 = [A, [B, [B, [B, A]]]],$$

$$D_5 = [B, [B, [A, [B, A]]]], \quad D_6 = [B, [B, [B, [B, A]]]].$$

Trotter-Suzuki decompositions

Omelyan's method

- Assume symmetric (not necessarily real) parameters ($a_1 = a_{q+1}$, $b_1 = b_q$)

$$e^{(A+B)h+O_1h+O_3h^3+O_5h^5} = e^{a_1Ah} e^{b_1Bh} \dots e^{b_qBh} e^{a_{q+1}Ah}$$

- Order $n = 4$ satisfied by:

$$\alpha(a_i, b_i) = \beta_i(a_i, b_i) = 0$$

- Order $n = 6$ satisfied by:

$$\gamma_j(a_i, b_i) = 0$$

$$O_1 = (\nu - 1)A + (\sigma - 1)B,$$

$$O_3 = \alpha C_1 + \beta C_2, \quad C_1 = [A, [A, B]], \quad C_2 = [B, [B, A]],$$

$$O_5 = \sum_{k=1}^6 \gamma_k D_k, \quad D_1 = [A, [A, [A, [A, B]]]], \quad D_2 = [A, [A, [B, [A, B]]]],$$

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Trotter-Suzuki decompositions

Omelyan's method

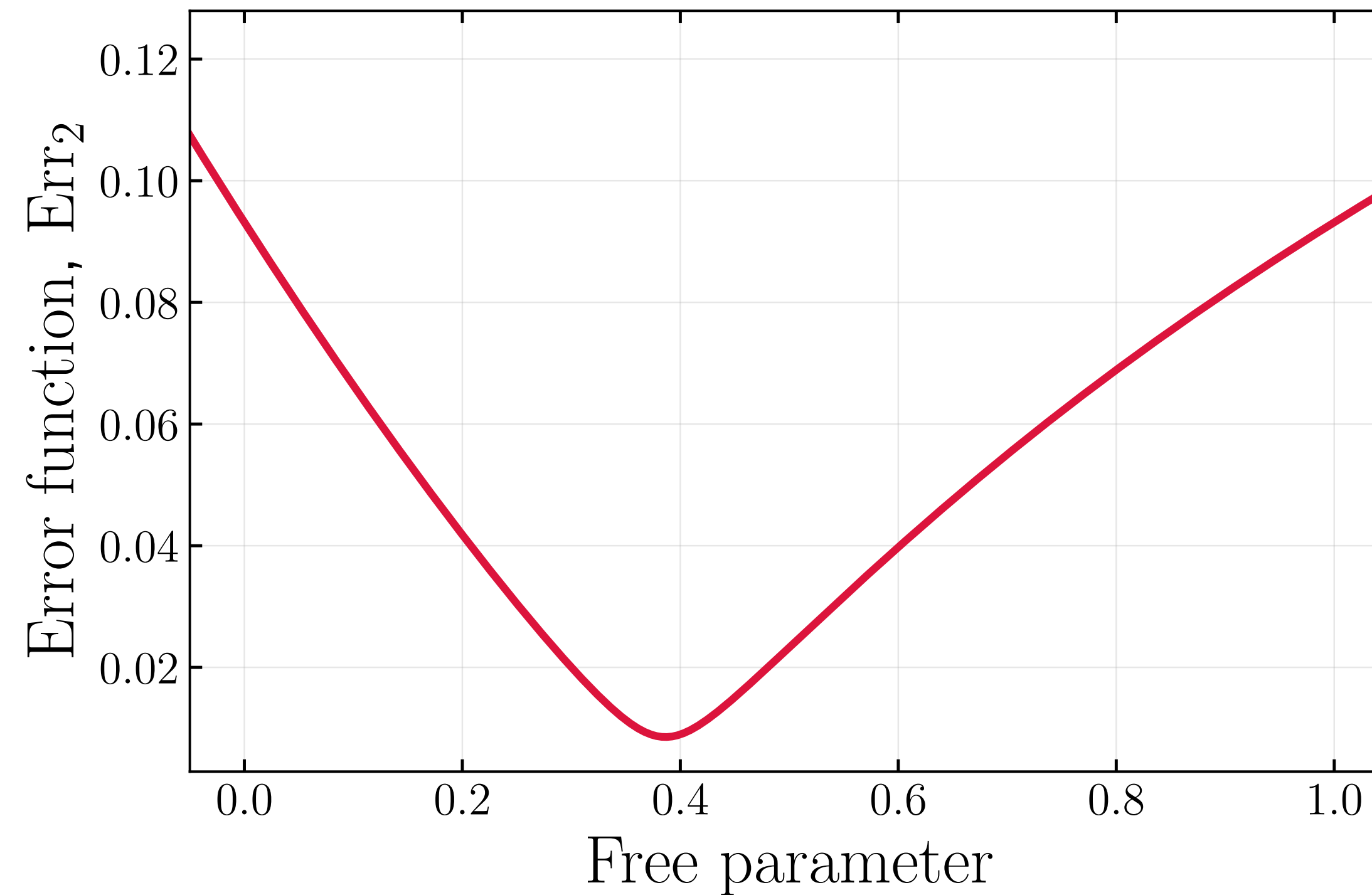
- "A decomposition is efficient if its leading order errors are small compared to the no. cycles q it requires"
- Error definition: $\text{Err}_2(a_i, b_i) = \sqrt{|\alpha|^2 + |\beta|^2}$, $\text{Err}_4(a_i, b_i) = \sqrt{\sum_{i=1}^6 |\gamma_i|^2}$,
where we assume orthogonality of the basis
- Efficiency definition: $\text{Eff}_2 = \frac{1}{q^2 \text{Err}_2}$, $\text{Eff}_4 = \frac{1}{q^4 \text{Err}_4}$

Trotter-Suzuki decompositions

Omelyan's method

- With increased order and no. cycles the error manifold complexity rises

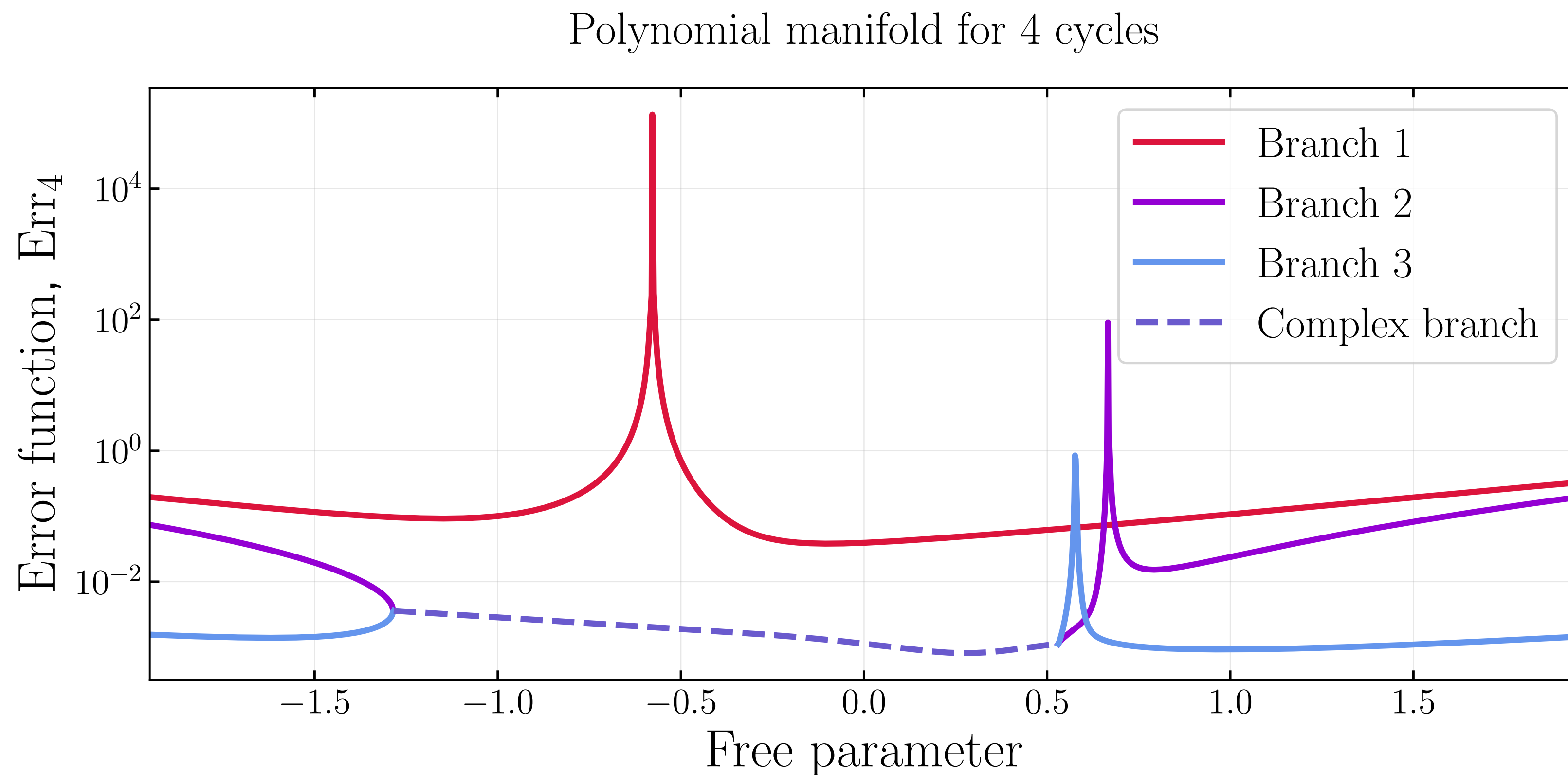
Polynomial manifold for 2 cycles



Trotter-Suzuki decompositions

Omelyan's method

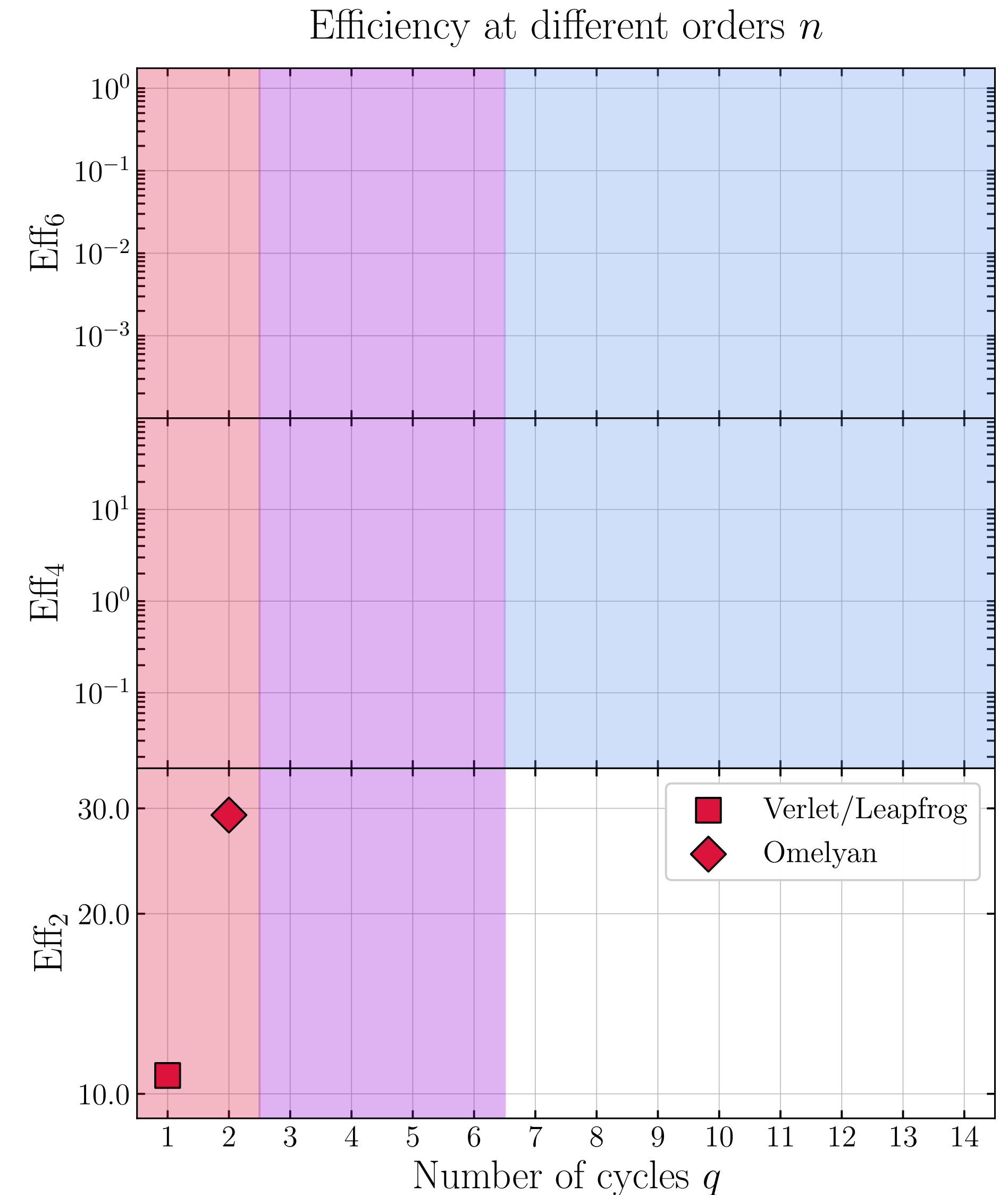
- With increased order and no. cycles the error manifold complexity rises



Efficiency results

Order 2

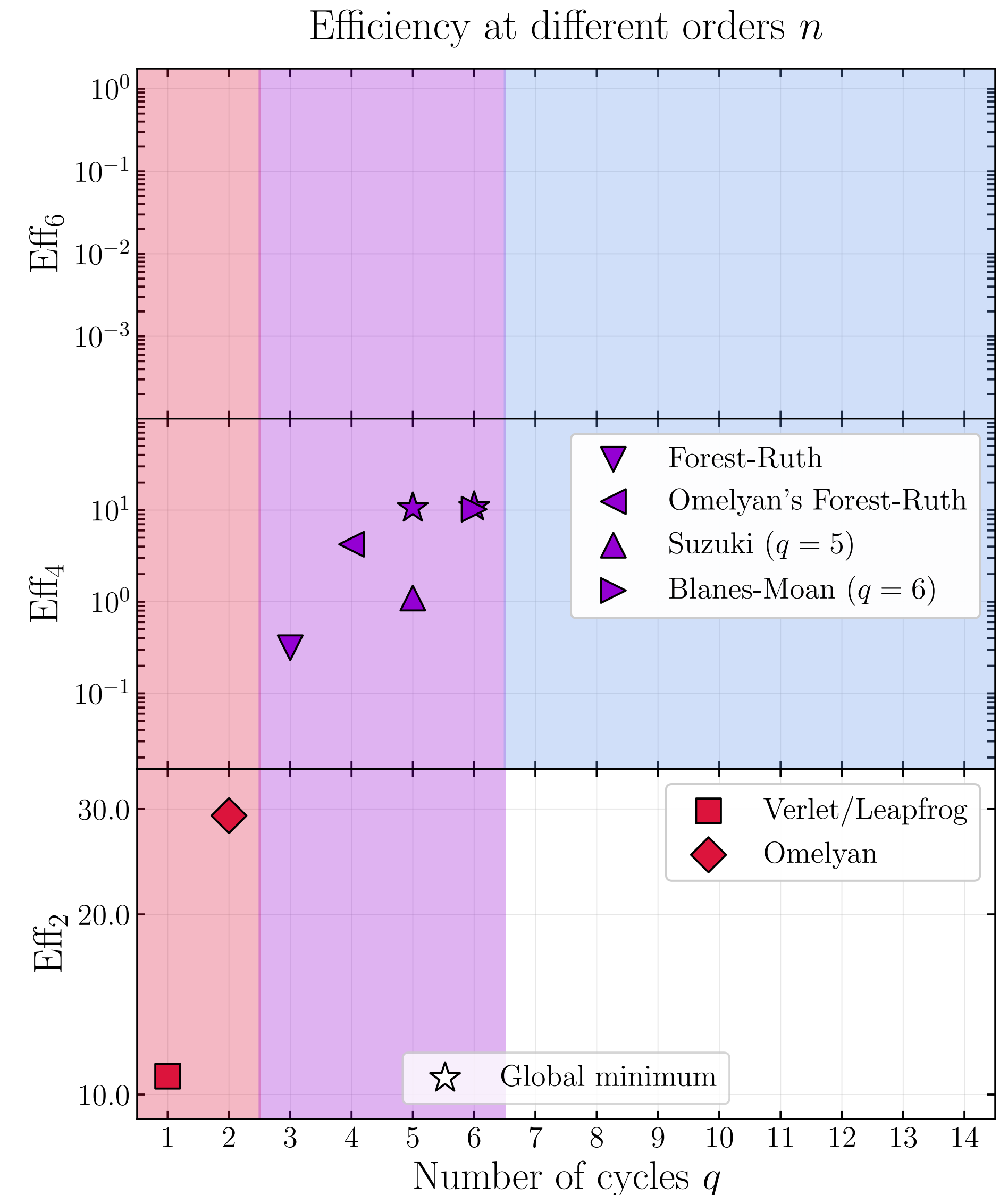
- Verlet or Leapfrog scheme ($q = 1$)
 - Simple, yet performs very well
 - Valid, if high precision is not desired
- Omelyan's scheme ($q = 2$)
 - One free parameter to optimize
 - Comparable to Leapfrog



Efficiency results

Order 4

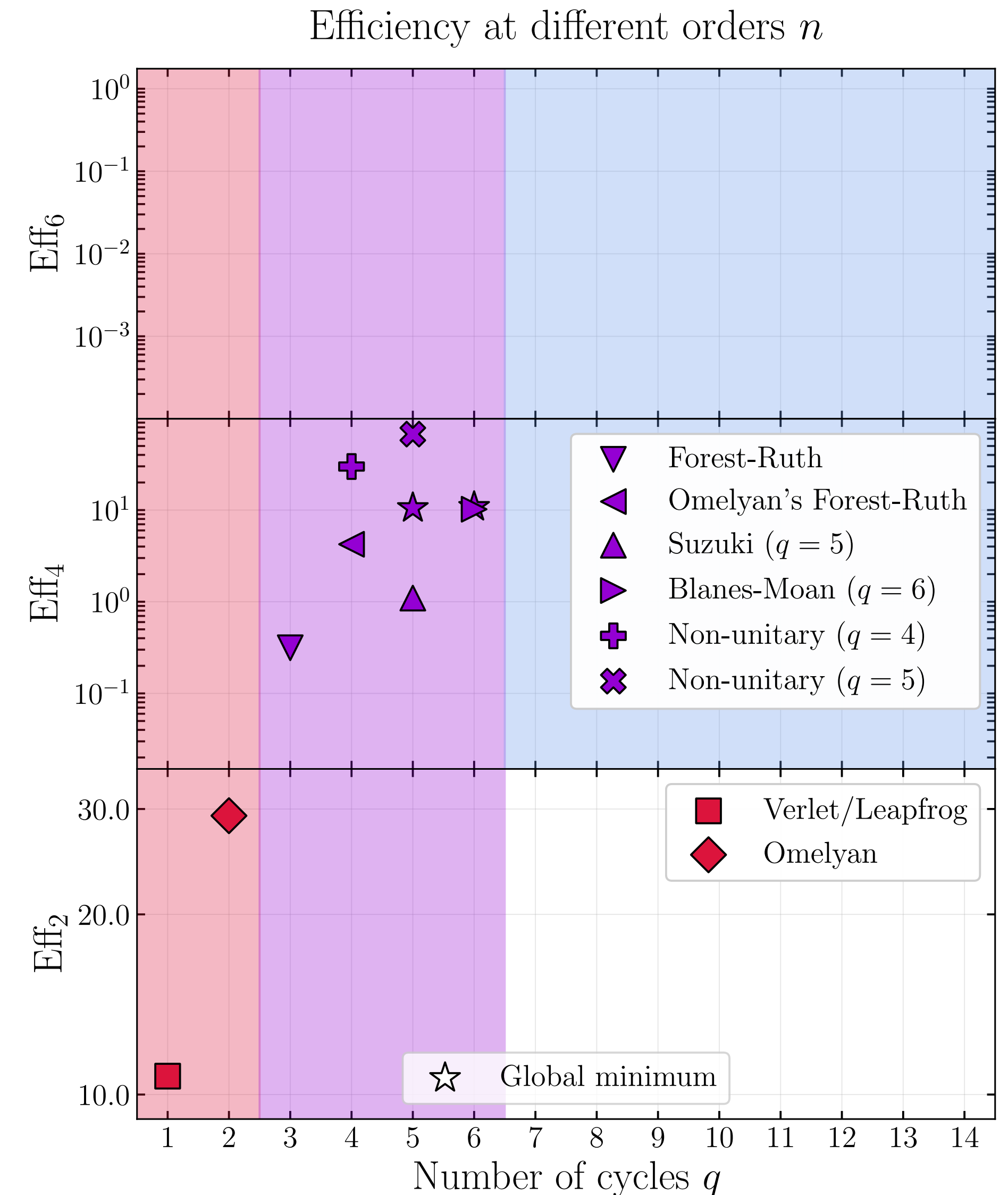
- Forest-Ruth scheme ($q = 3$)
 - Poor performance
- Omelyan's Forest-Ruth scheme ($q = 4$)
 - One free parameter
- Suzuki's scheme ($q = 5$)
 - Favourable error accumulation
- Blanes-Moan ($q = 6$)
 - Highly efficient order 4 scheme



Efficiency results

Order 4

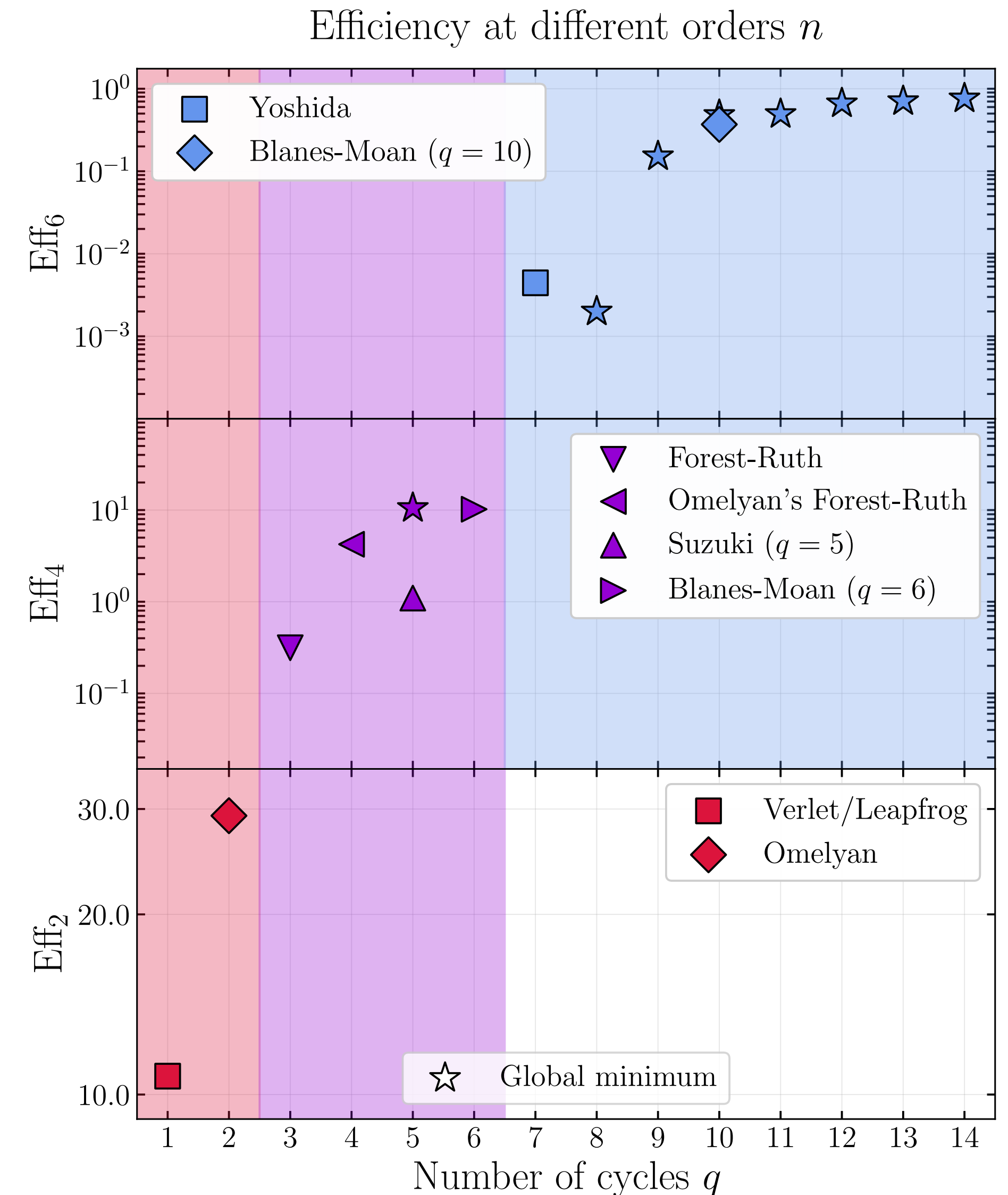
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Efficiency results

Order 6

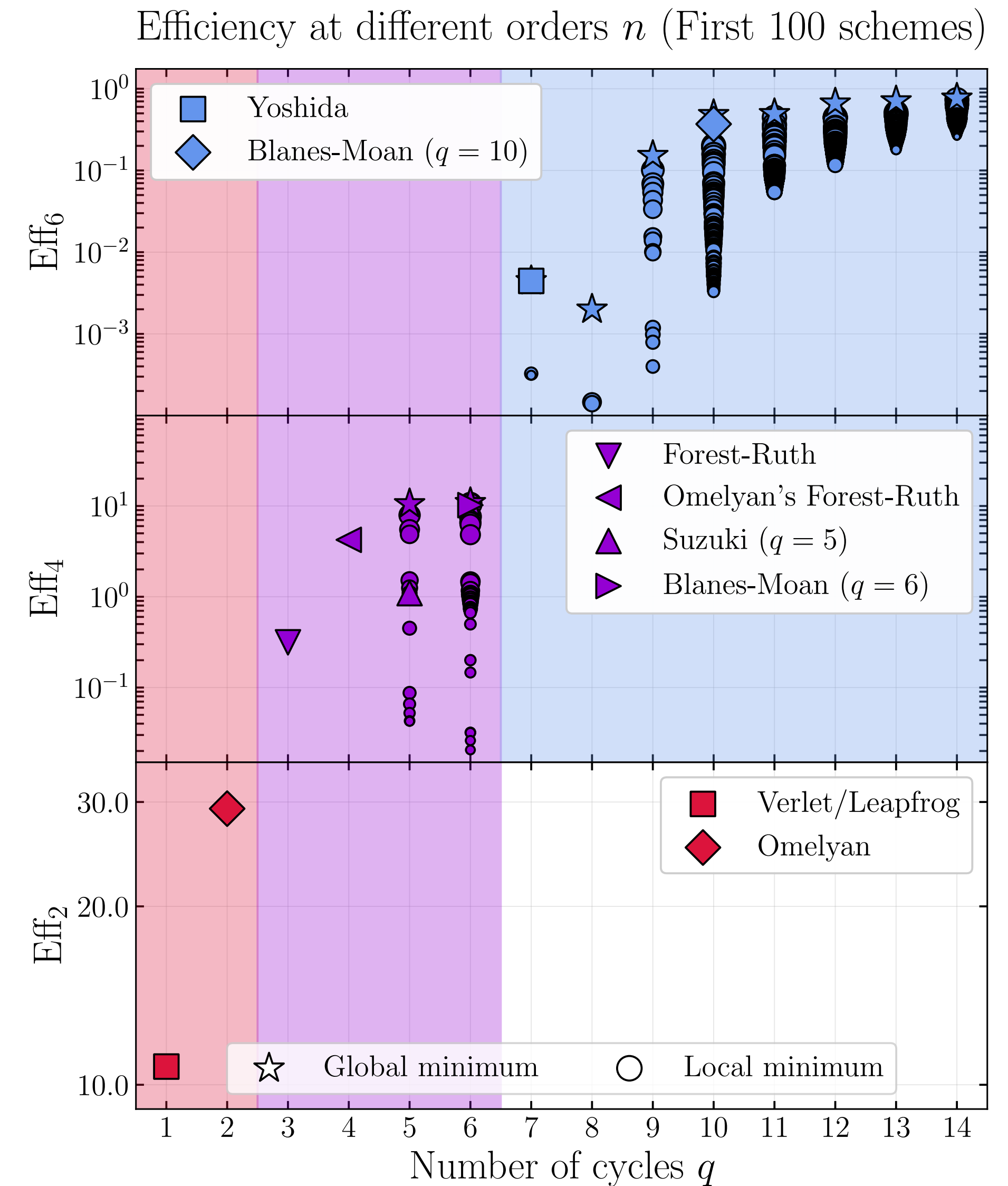
- Yoshida ($q = 7$)
 - Unusual scheme ($n_p = 8, n_c = 10$)
 - Extremely poor efficiency
- Blanes-Moan ($q = 10$)
 - One of the best order 6 schemes
- New found schemes
 - Improvement over the known schemes



Efficiency results

Order 6

- Yoshida ($q = 7$)
 - Unusual scheme ($n_p = 8, n_c = 10$)
 - Extremely poor efficiency
- Blanes-Moan ($q = 10$)
 - One of the best order 6 schemes
- New found schemes
 - Improvement over the known schemes
 - Also explored the local minima



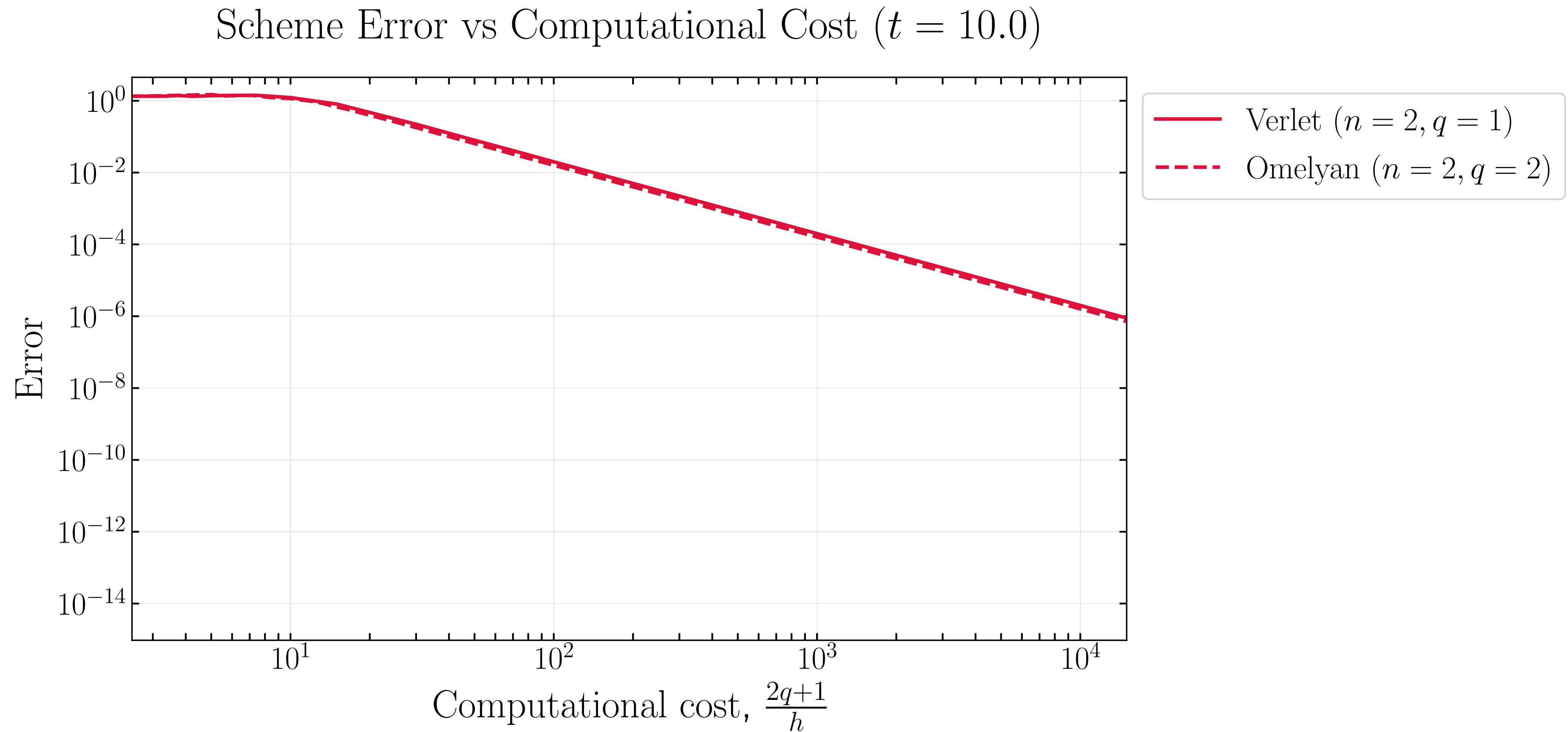
Numerical experiments

- The Heisenberg XXZ model: $H = \sum_{i=1}^L (J^x \sigma_i^x \sigma_{i+1}^x + J^y \sigma_i^y \sigma_{i+1}^y + J^z \sigma_i^z \sigma_{i+1}^z + h_i \sigma_i^z), J^\alpha = 1$
- Correspondence with quantum computers (local gates)
- Periodic spin chain of length $L = 6$
- Estimate error using the Frobenius norm:

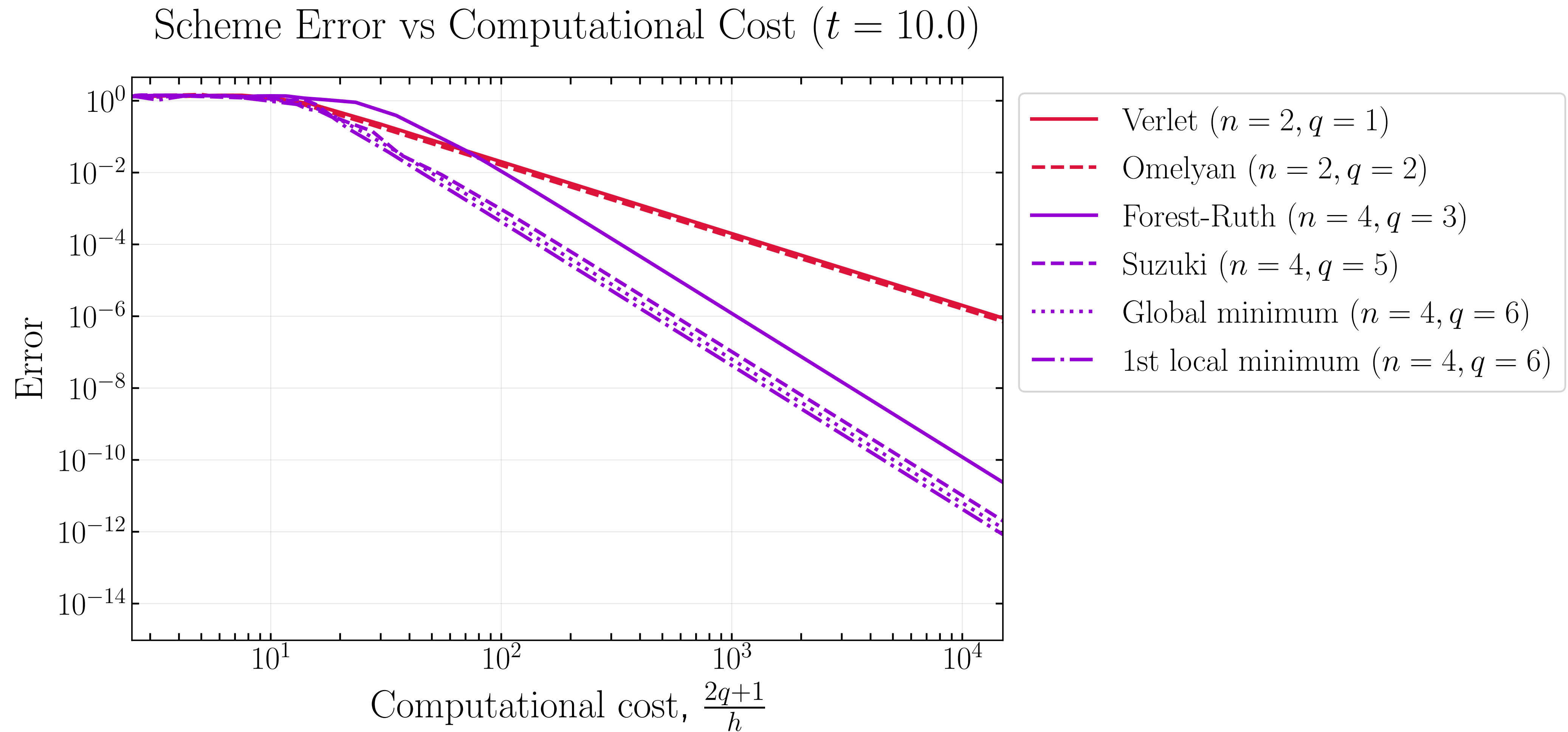
$$\text{Error}(t) = \|U(t) - S(h)^{t/h}\|_F, \quad U(t) \approx [S(h)]^{t/h}$$

Evolve until time $t = 10.0$, using some time step h

Numerical experiments

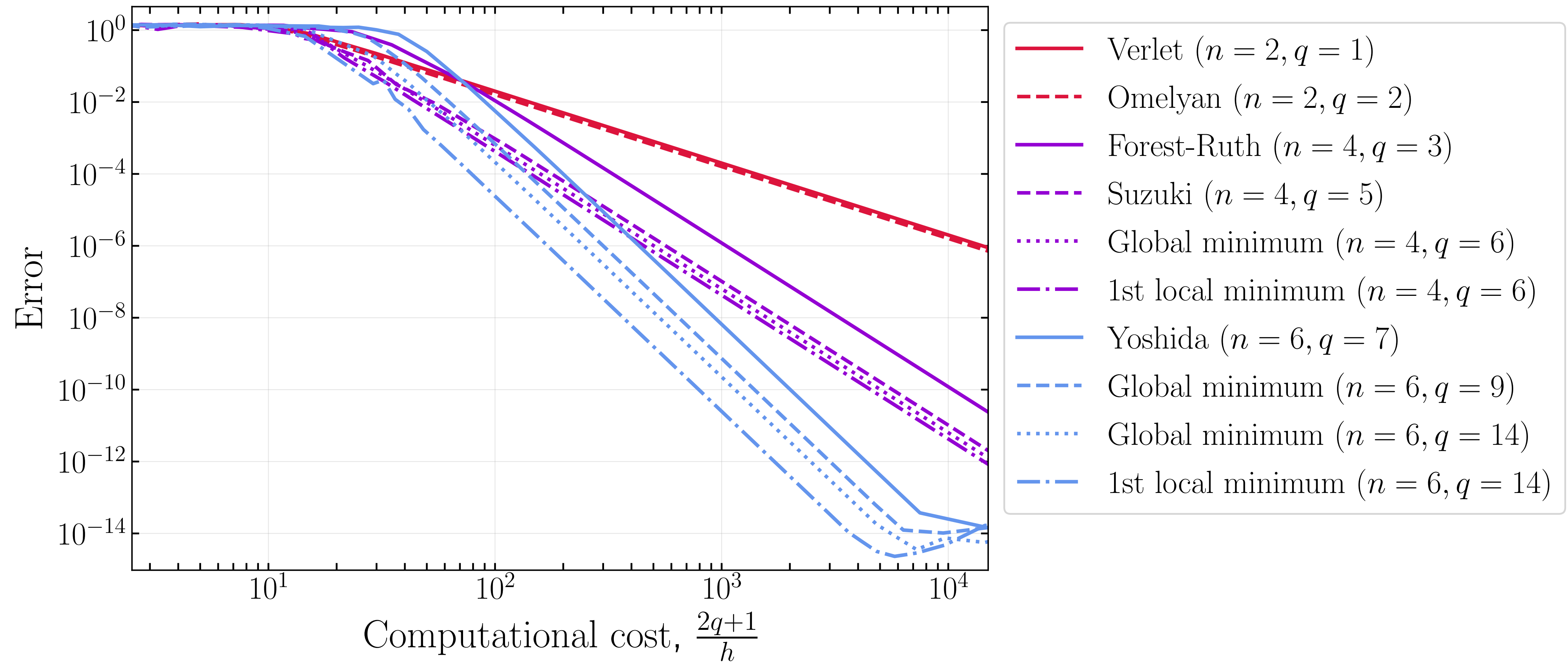


Numerical experiments

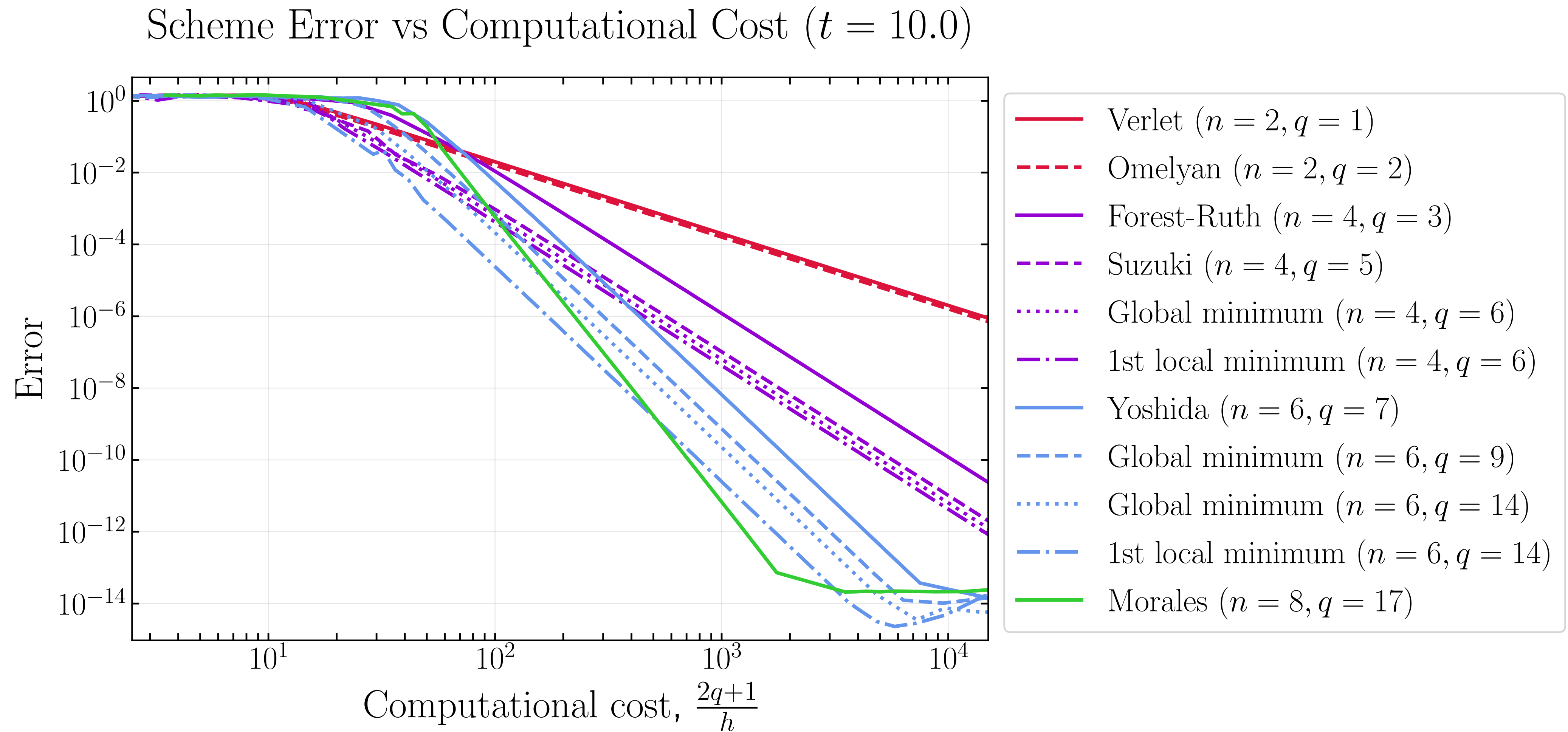


Numerical experiments

Scheme Error vs Computational Cost ($t = 10.0$)



Numerical experiments



Numerical experiments

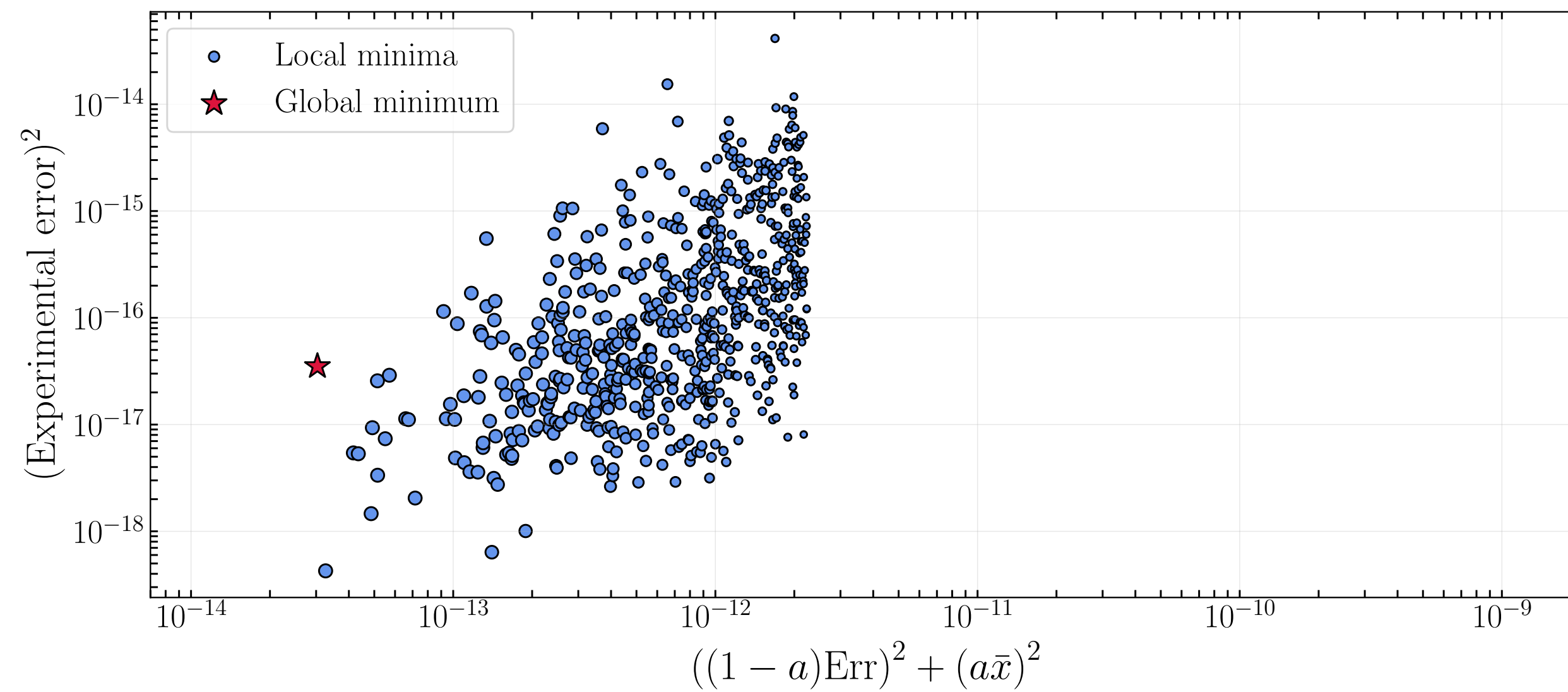
- Correspondence between the experimental and theoretical error is not exact
- Investigate the properties of the parameters (a_i, b_i)
- Optimally: All parameters are exactly the same: $a_i = b_i = x_{\text{opt.}}$, $x_{\text{opt.}} = \frac{1}{q}$
- Add a term to the theoretical error function:

$$((1 - a)\text{Err})^2 + (a\bar{x})^2$$

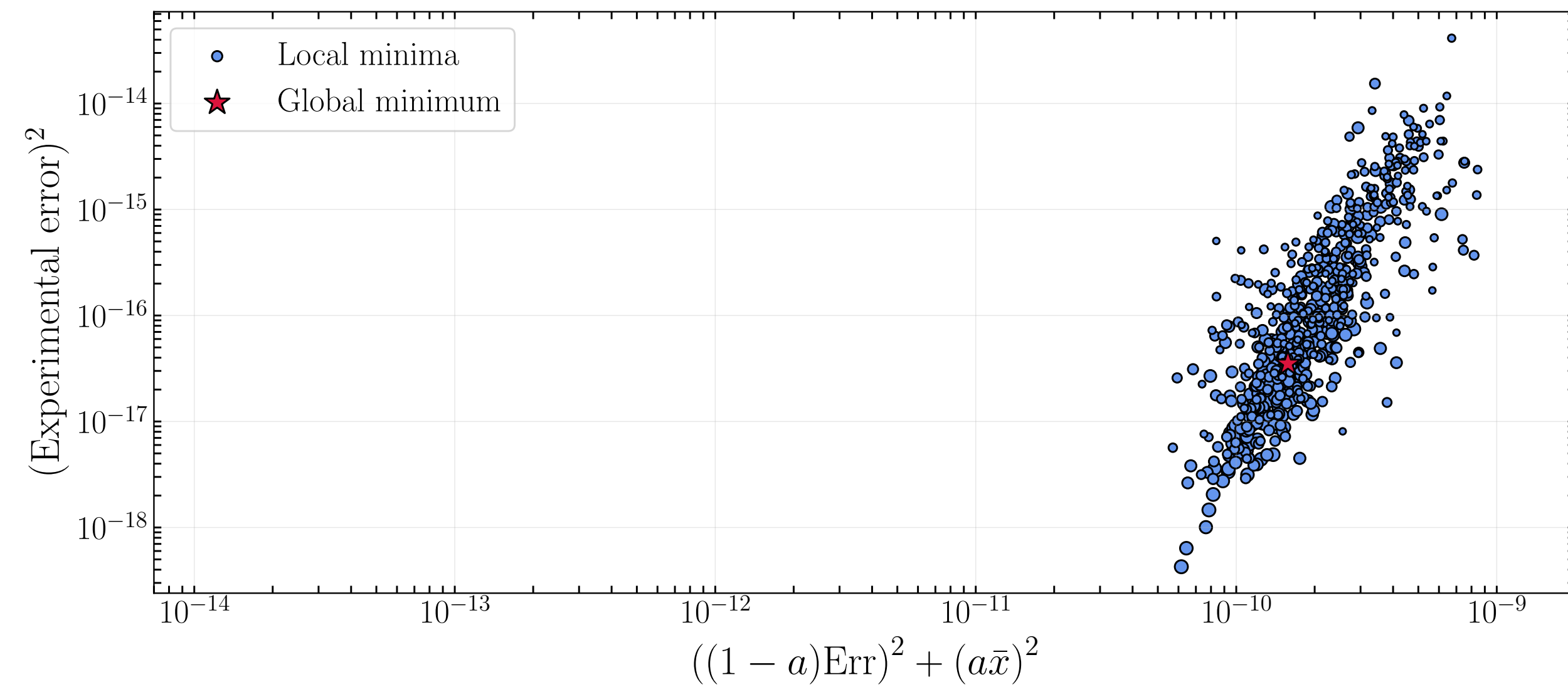
$$\bar{x} = \sum_i (a_i - x_{\text{opt.}}) + \sum_i (b_i - x_{\text{opt.}})$$

Numerical experiments

Error comparison at 14 cycles, $a = 0.000 \times 10^0$

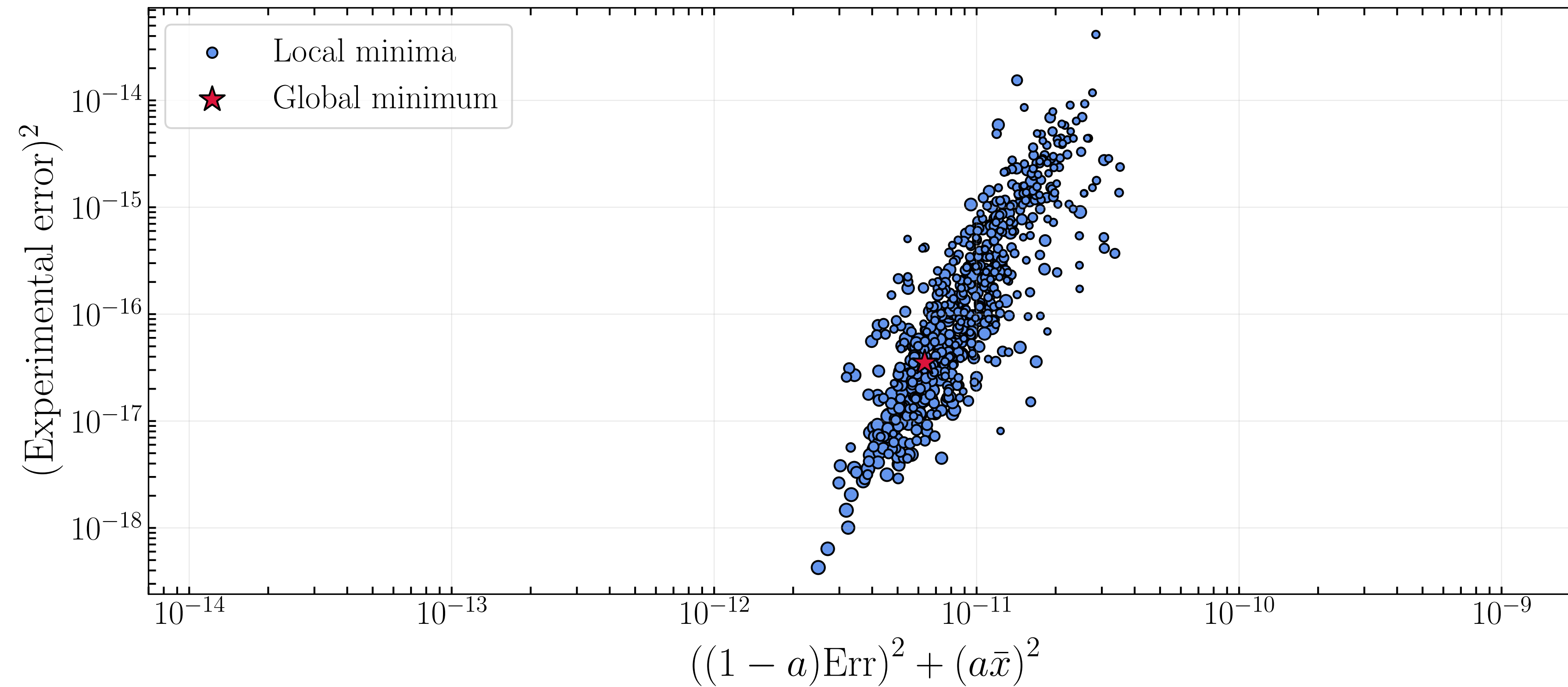


Error comparison at 14 cycles, $a = 1.000 \times 10^{-5}$



Numerical experiments

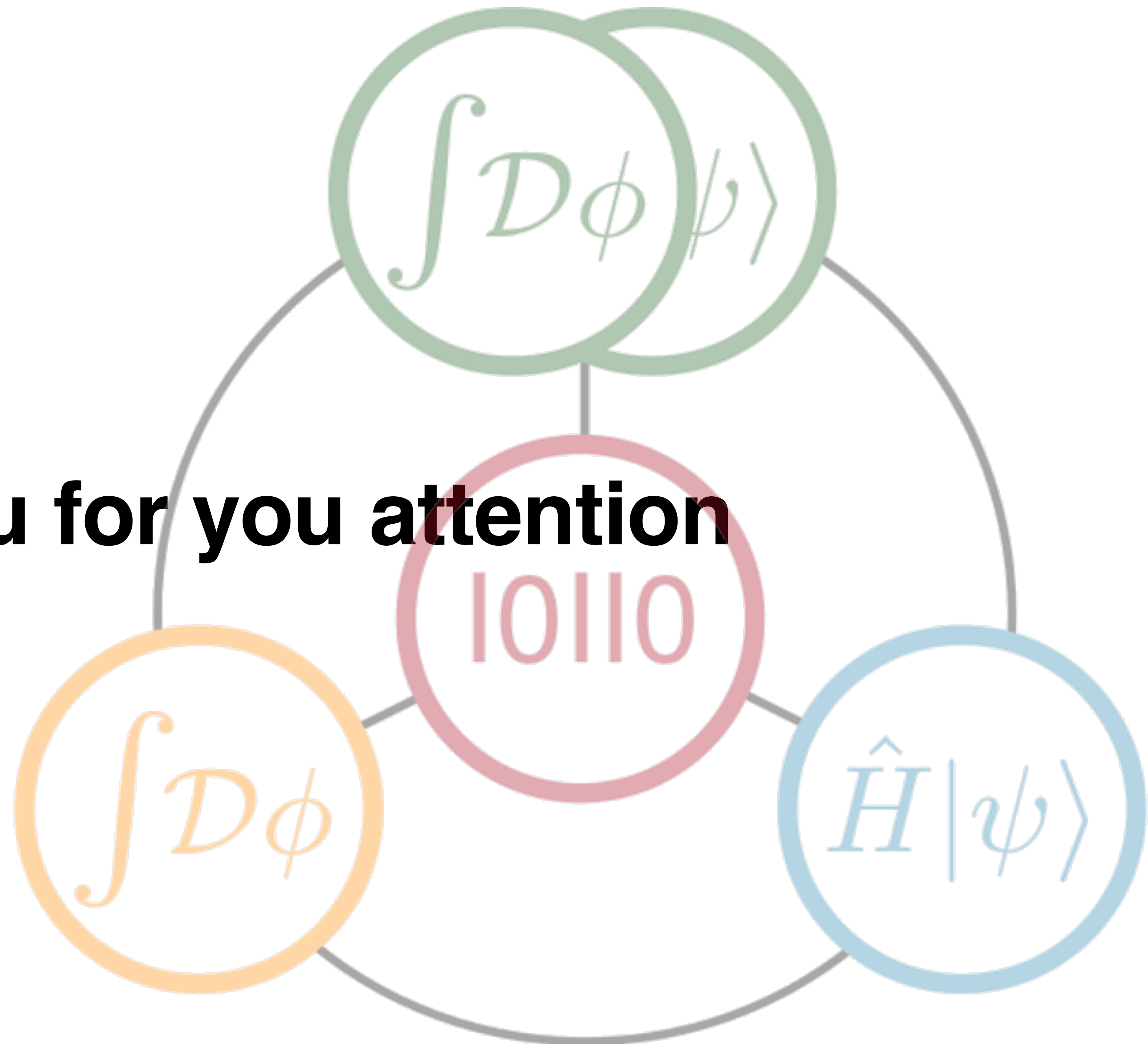
Error comparison at 14 cycles, $a = 2.000 \times 10^{-6}$



Outlook and future work

- We extended Omelyan's method to a general framework for optimizing Trotter-Suzuki decompositions and found novel schemes
- In progress: - Theoretical-Experimental error correspondence
 - Order 8 scheme optimization
 - Research of non-unitary schemes with complex parameters
- Future work: - Order 10 recursive formulae
 - Test optimized schemes on quantum hardware

Thank you for your attention

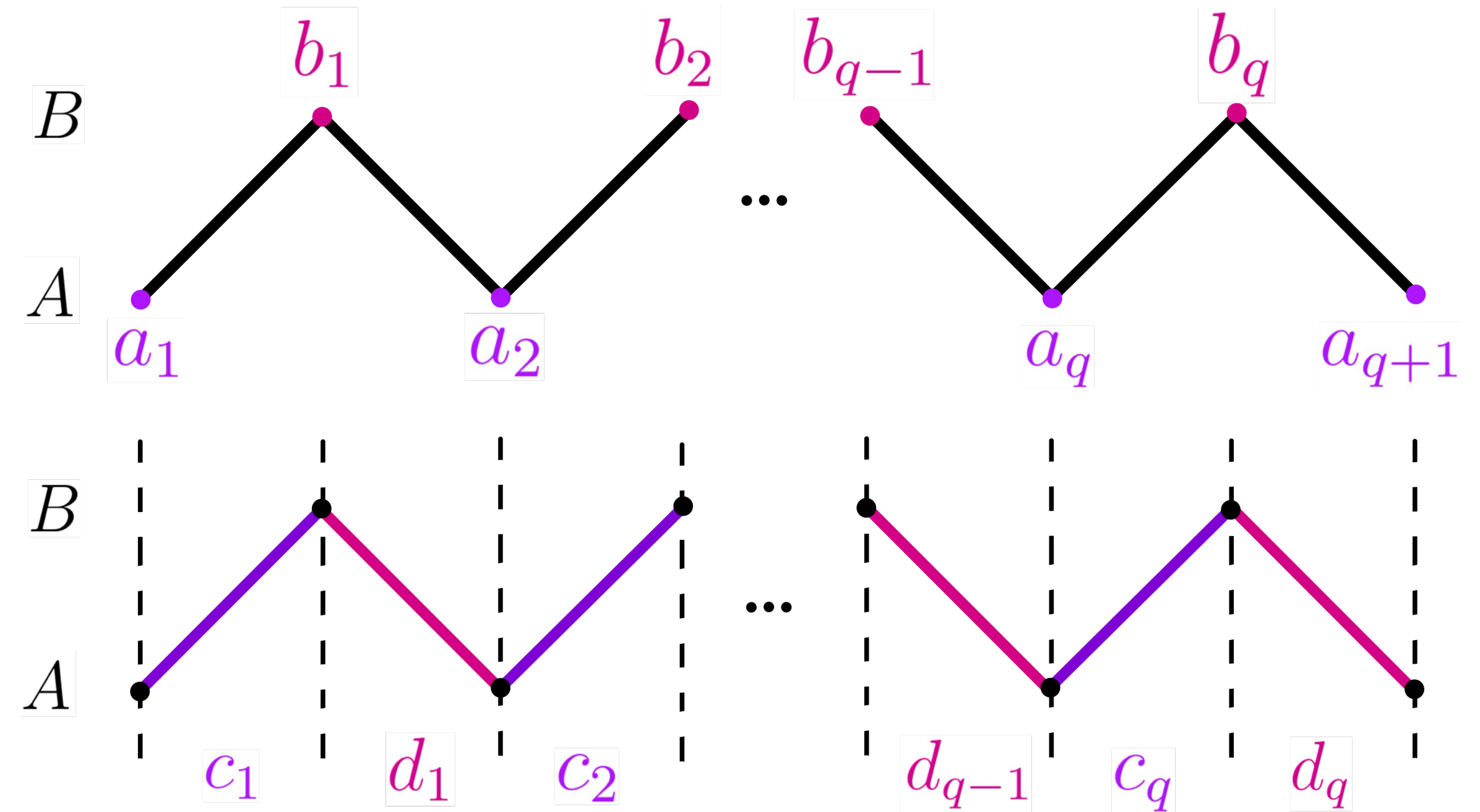


Additional slides

Arbitrary no. stages adaptation

- Every scheme with 2 stages is applicable to an arbitrary no. stages
- Transition from stage-based to a ramp based approach:

$$\begin{array}{ll}
 c_1 = a_1, & d_1 = b_1 - c_1, \\
 \vdots & \vdots \\
 c_i = a_i - d_{i-1}, & d_i = b_i - c_i
 \end{array}$$



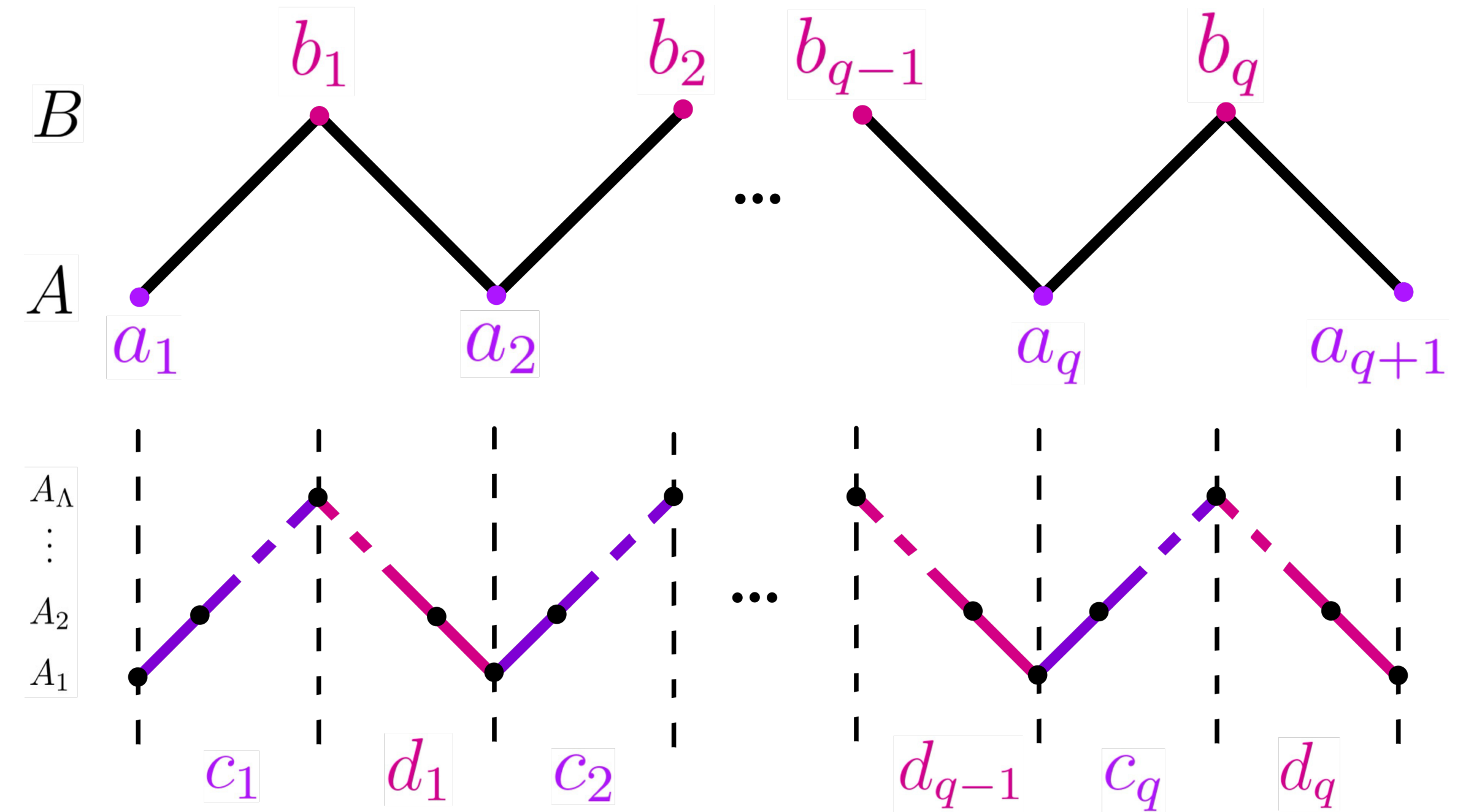
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$$\begin{aligned} c_1 &= a_1, & d_1 &= b_1 - c_1, \\ \vdots & & \vdots & \\ c_i &= a_i - d_{i-1}, & d_i &= b_i - c_i \end{aligned}$$

$$e^{h \sum_{k=1}^{\Lambda} A_k} + \mathcal{O}(h^{n+1}) = \left(\prod_{k=1}^{\Lambda} e^{A_k c_1 h} \right) \left(\prod_{k=\Lambda}^1 e^{A_k d_1 h} \right) \dots \left(\prod_{k=1}^{\Lambda} e^{A_k c_q h} \right) \left(\prod_{k=\Lambda}^1 e^{A_k d_q h} \right)$$



Additional slides

Framework details

- Coefficients α , β and γ_j are polynomials of parameters a_i, b_i

$$e^{(A+B)h+O_1h+O_3h^3+O_5h^5} = e^{\frac{a_2}{2}Ah} e^{\frac{b_1}{2}Bh} e^{a_1Ah} e^{\frac{b_1}{2}Bh} e^{\frac{a_2}{2}Ah}$$

- Denote a scheme $\Phi^{(i_A, i_B)}$ at iteration (i_A, i_B)

$$e^{\frac{a_2}{2}Ah} e^{\frac{b_1}{2}Bh} e^{a_1Ah} e^{\frac{b_1}{2}Bh} e^{\frac{a_2}{2}Ah} \rightarrow e^{\frac{a_2}{2}Ah} e^{\Phi^{(1,1)}} e^{\frac{a_2}{2}Ah} \rightarrow e^{\Phi^{(2,1)}}$$

- General form:

$$\Phi^{(i_A, i_B)} = \left(\nu^{(i_A)} A + \sigma^{(i_B)} B \right) h + \left(\alpha^{(i_A, i_B)} C_1 + \beta^{(i_A, i_B)} C_2 \right) h^3 + h^5 \sum_k \gamma_k^{(i_A, i_B)} D_k + \dots$$

$$\text{where: } \nu^{(i_A)} = \sum_{i=1}^{i_A} a_i, \quad \sigma^{(i_B)} = \sum_{i=1}^{i_B} b_i$$

Additional slides

Framework details

- Use the BCH formula to derive the recursive formulae for the coefficients $e^{\Phi(i,i-1)} = e^{\frac{a_i}{2}Ah} e^{\Phi(i-1,i-1)} e^{\frac{a_i}{2}Ah}$

- Order 2 coefficients recursive formulae:

$$\alpha^{(i,i-1)} = \alpha^{(i-1,i-1)} + \alpha a_i^2 \sigma^{(i-1)} - \beta a_i \nu^{(i-1)} \sigma^{(i-1)},$$

$$\beta^{(i,i-1)} = \beta^{(i-1,i-1)} + \beta a_i \left(\sigma^{(i-1)} \right)^2$$

- Higher order derivations become much more involved

Additional slides

Framework details

- The error function defines a high-dimensional manifold in parameters a_i and b_i
- Dimension: $n_p = q + 1, n_c \in (2, 4, 10, \dots)$
- Goal: minimize this manifold to identify global and local minima

$$\text{Err}_2(a_i, b_i) = \sqrt{|\alpha|^2 + |\beta|^2}$$

$$\text{Err}_4(a_i, b_i) = \sqrt{\sum_{k=1}^6 |\gamma_k|^2}$$

Additional slides

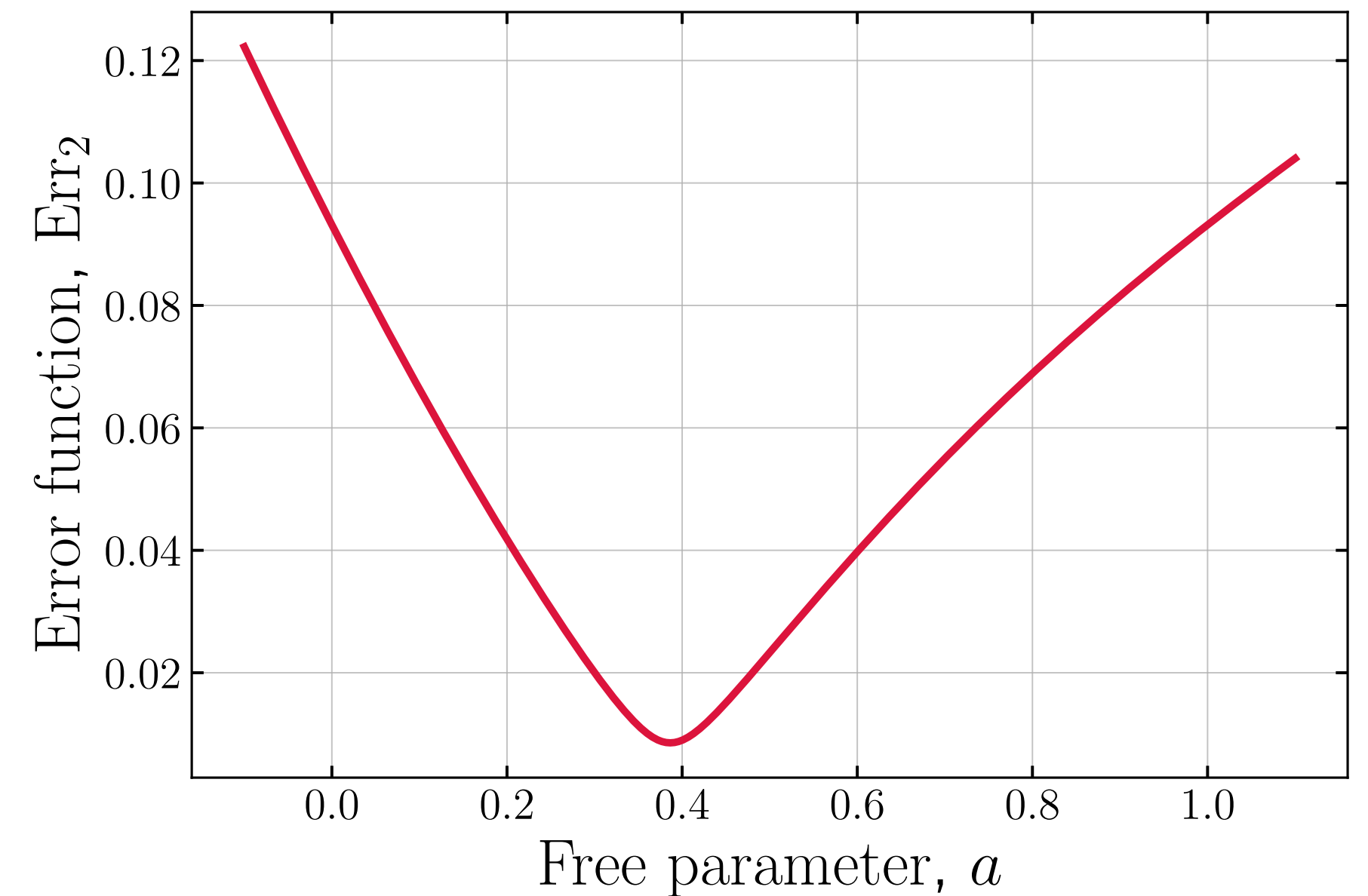
Framework details

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- Dimension: $n_p = q + 1, n_c \in (2, 4, 10, \dots)$
- Goal: minimize this manifold to identify global and local minima
- Example: $q=2$, 1 free parameter

$$\alpha(q=2) = \frac{a^2}{8} - \frac{a}{4} + \frac{1}{12}, \quad \beta(q=2) = -\frac{a}{8} + \frac{1}{24}$$

$$\text{Err}_2(a_i, b_i) = \sqrt{|\alpha|^2 + |\beta|^2}$$

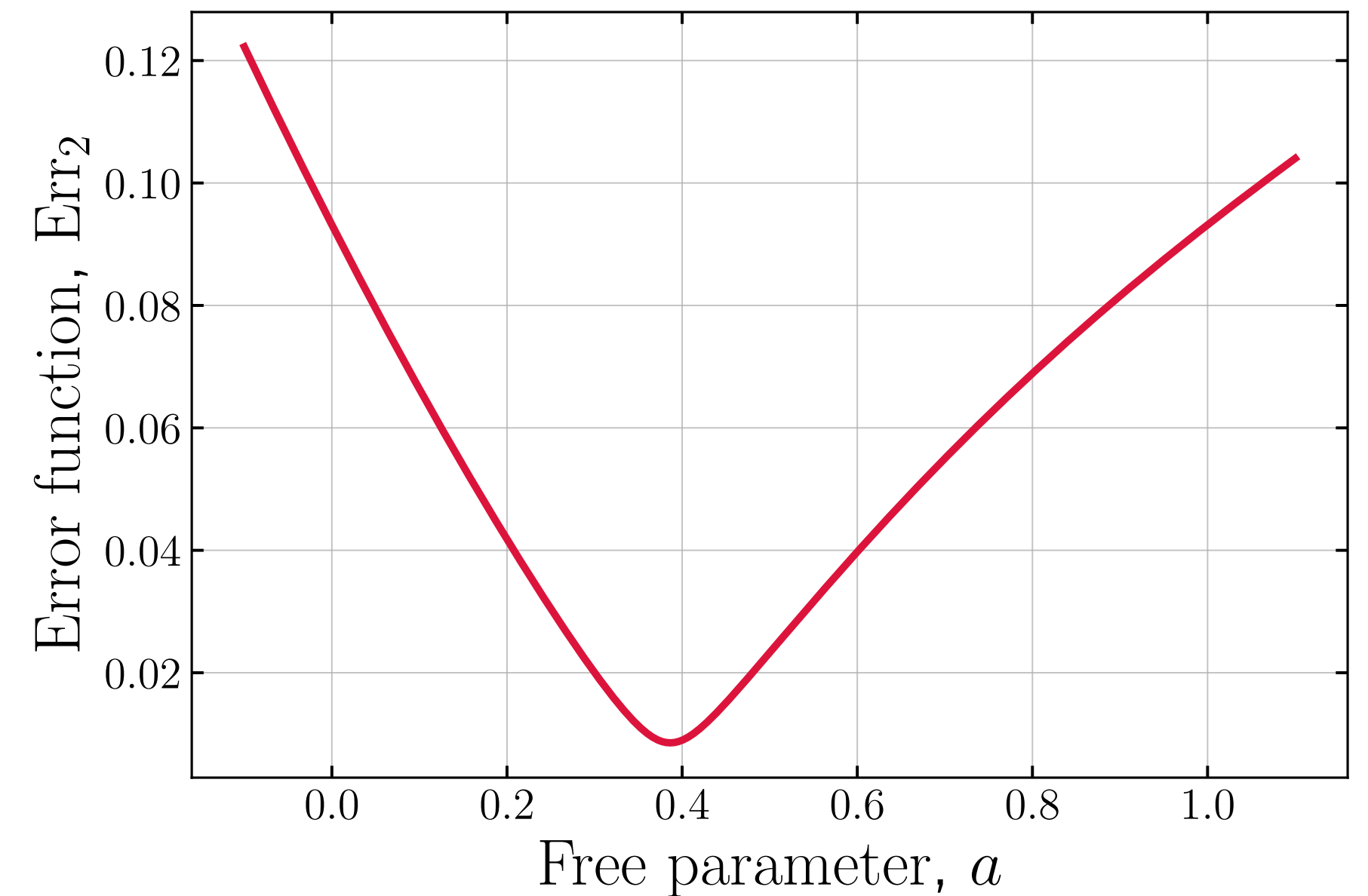
$$\text{Err}_4(a_i, b_i) = \sqrt{\sum_{k=1}^6 |\gamma_k|^2}$$



Additional slides

Framework details

- Optimization method: The Levenberg-Marquard algorithm
- Combination of the Gradient descent and the Gauss-Newton method
- Gradient descent: quickly accelerates toward the minimum region
- Gauss-Newton: Assumes the minimum region and accurately pinpoints the minimum
- Fast convergence, but susceptible to local minima → Many random initial parameters

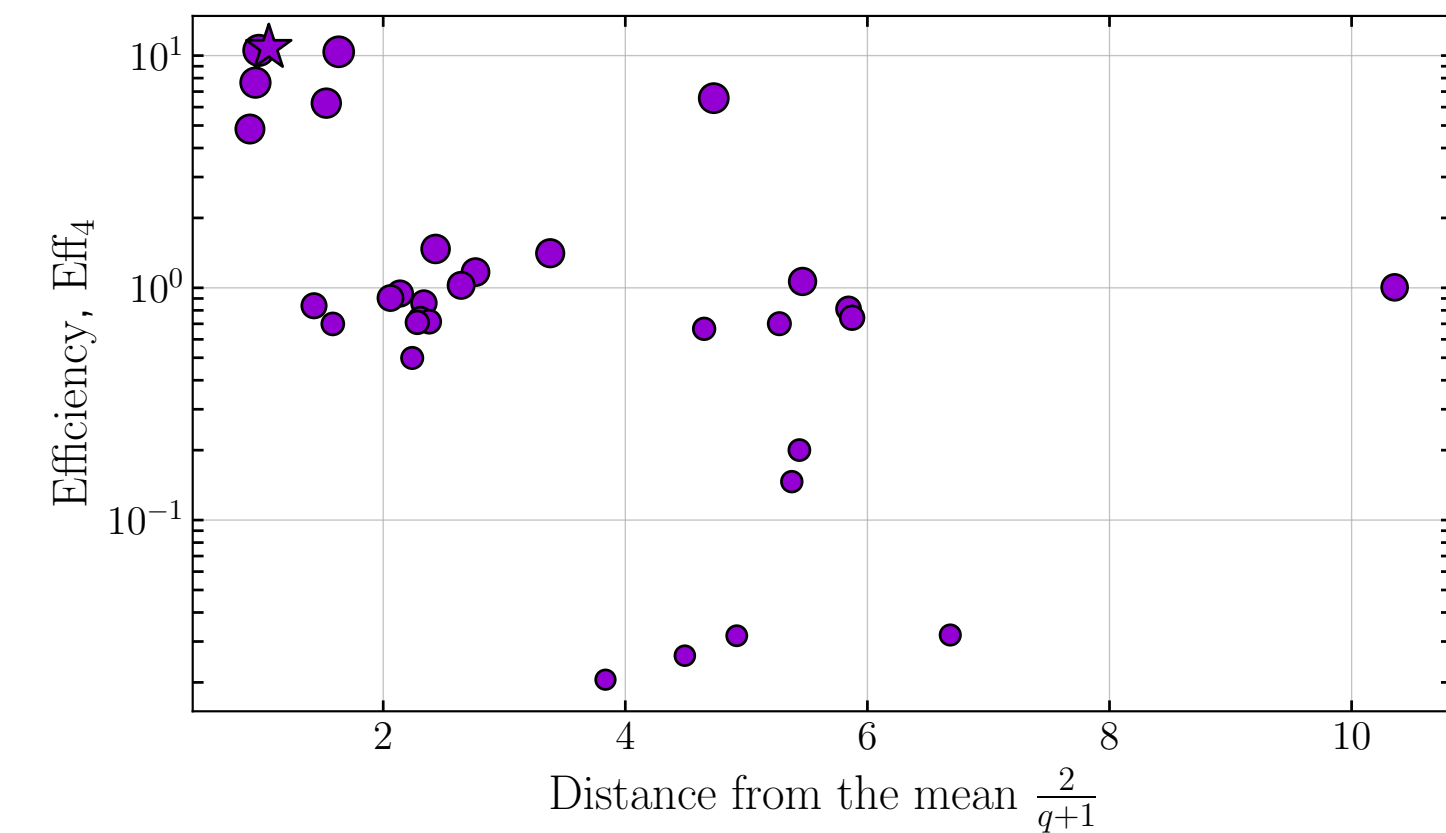


Additional slides

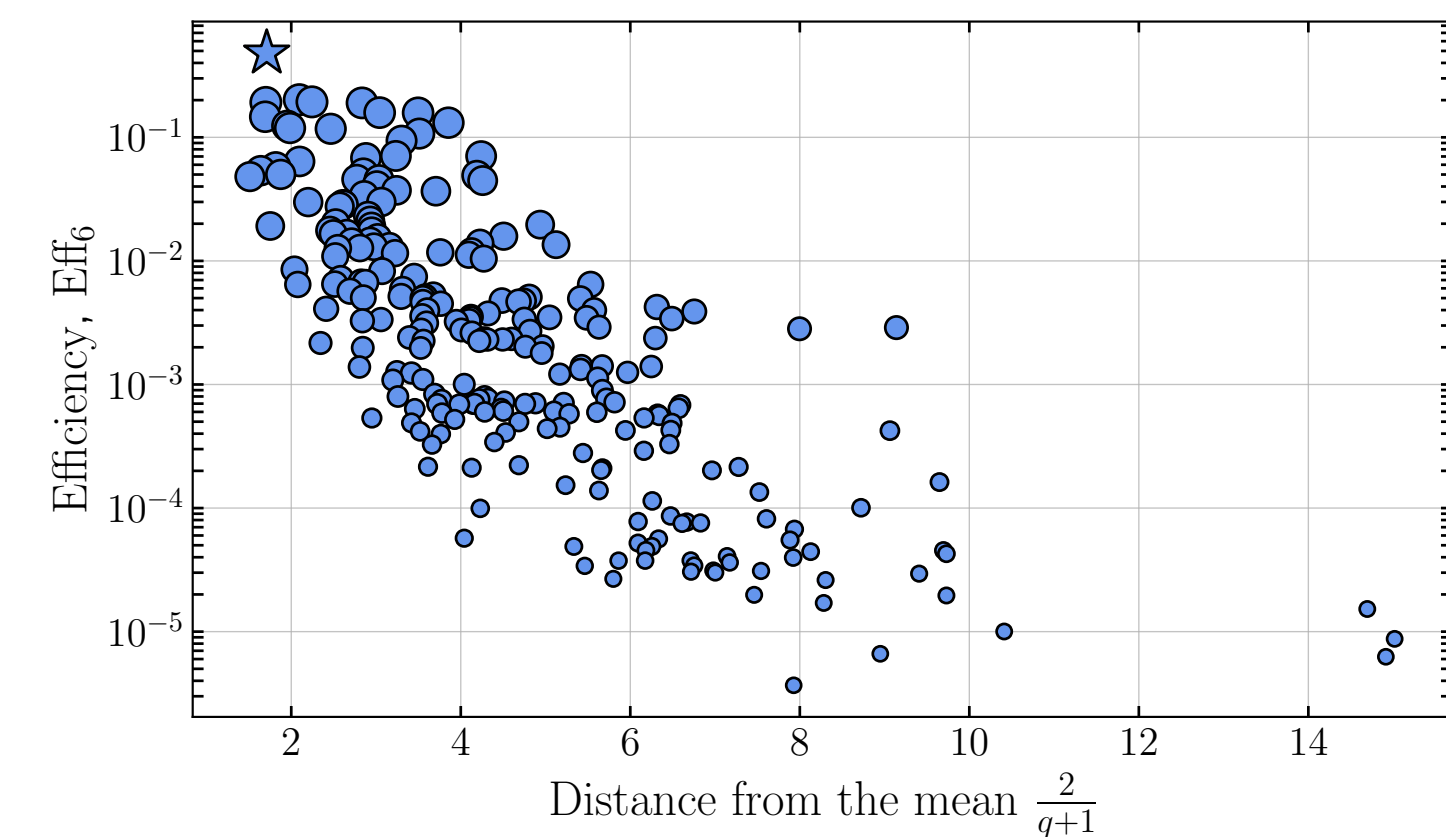
Local minima

- Global minimum is usually close to the average parameter value $\frac{2}{q+1}$
- Efficiency drops drastically far from this mean
- It is good to study less efficient schemes, which are closer to the mean

Found Schemes (Minima) at 6 cycles, Order $n = 4$



Found Schemes (Minima) at 10 cycles, Order $n = 6$

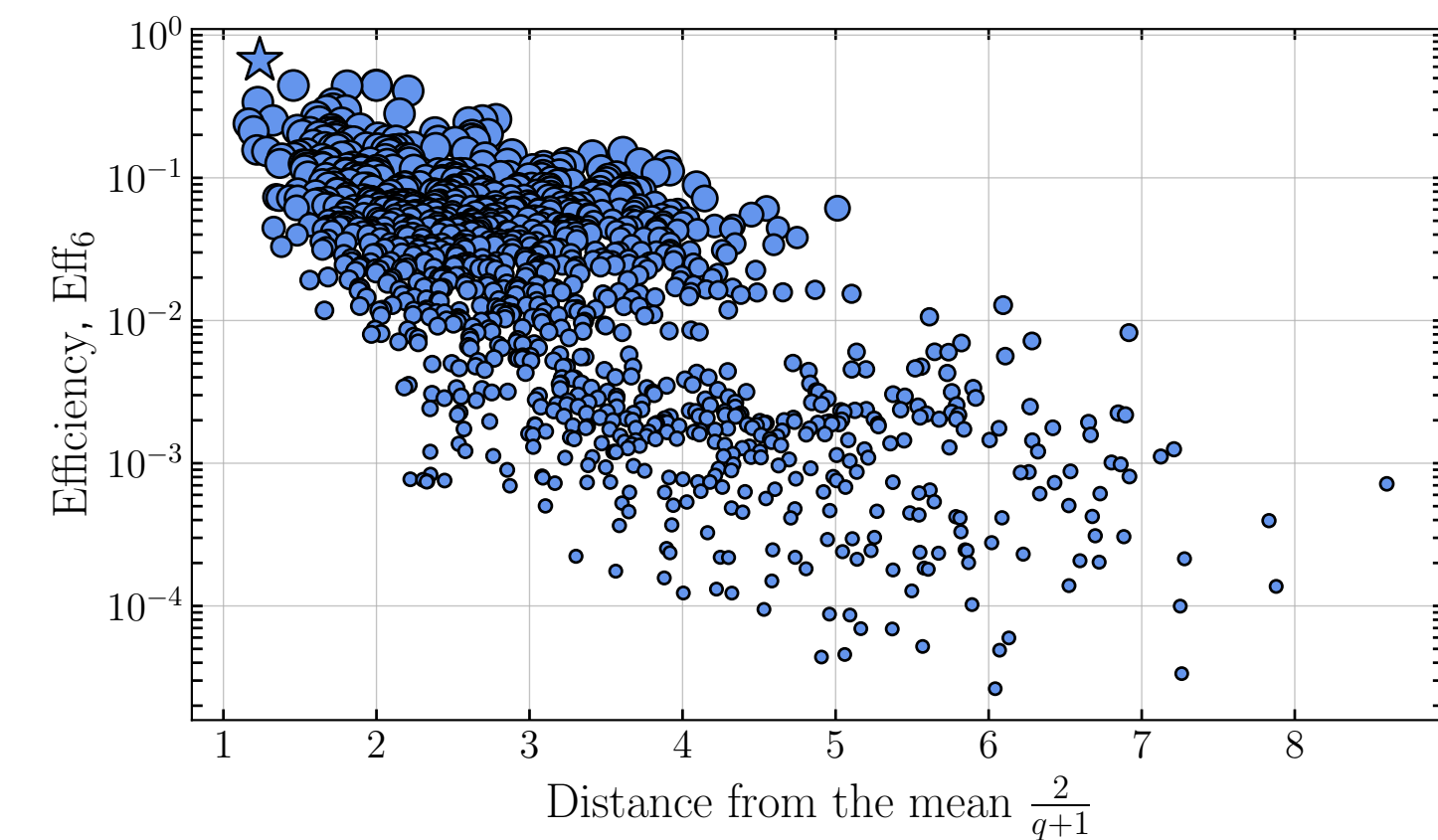


Additional slides

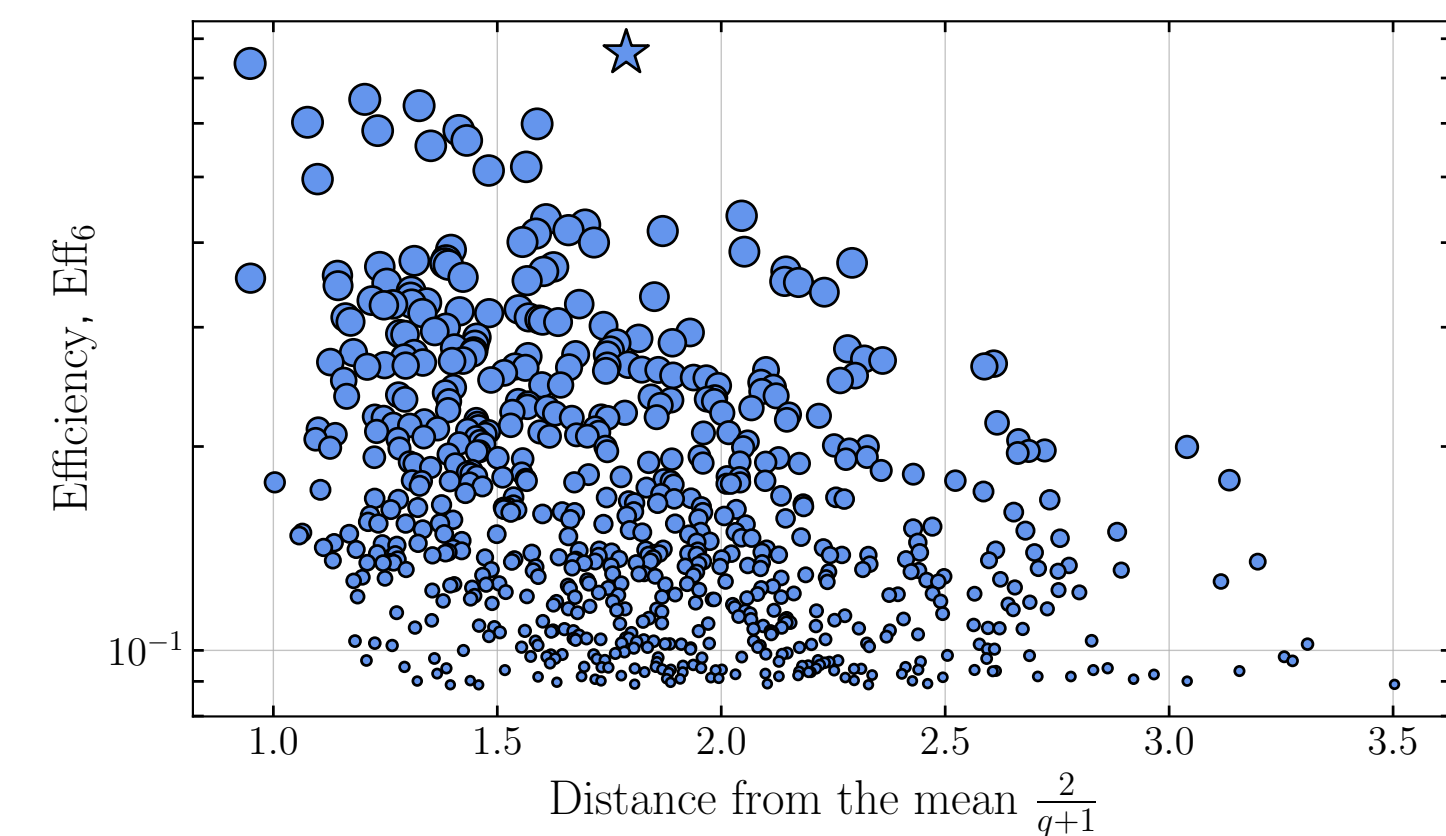
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Found Schemes (Minima) at 12 cycles, Order $n = 6$

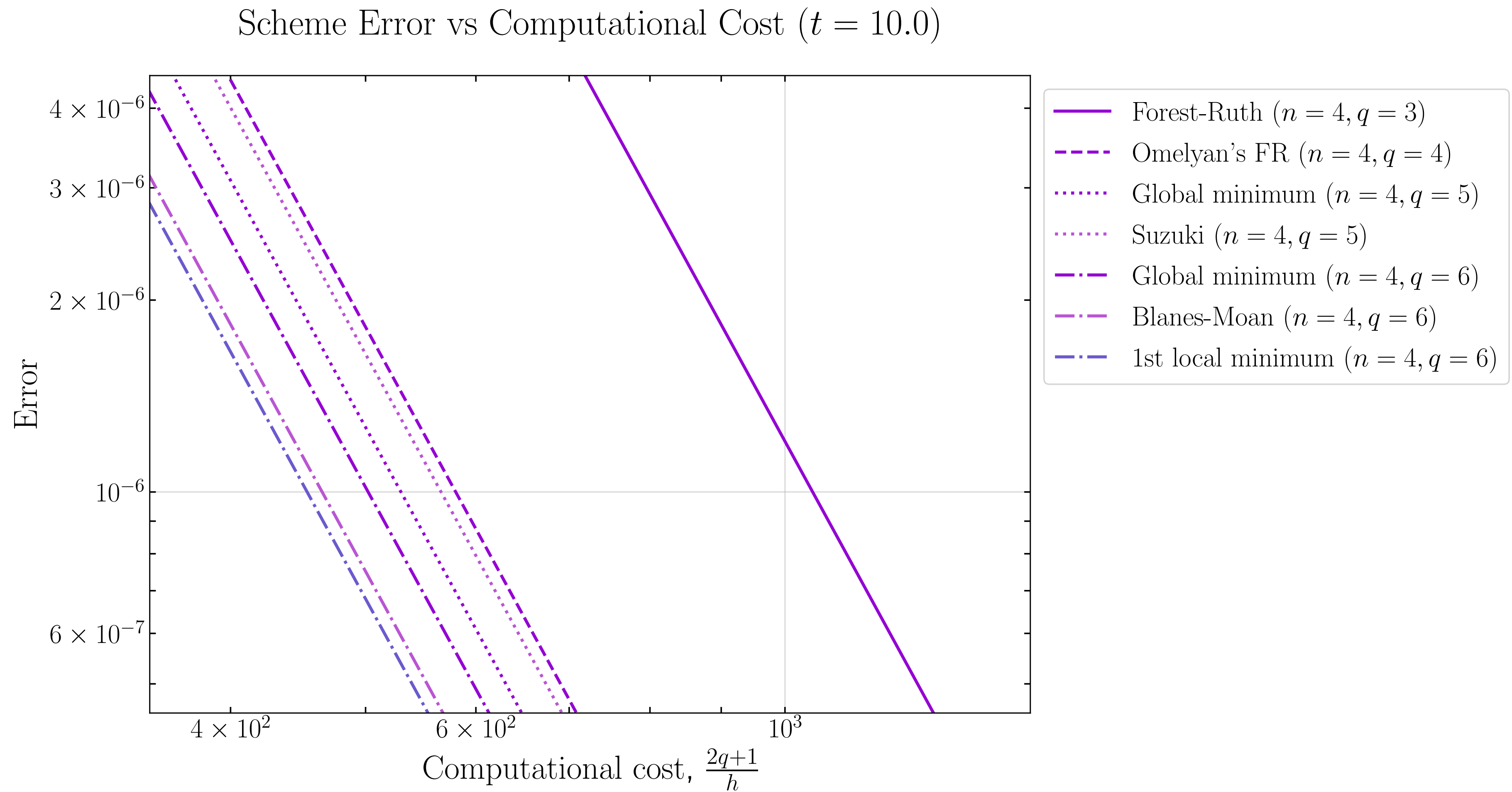


Found Schemes (Minima) at 14 cycles, Order $n = 6$



Additional slides

Numerical experiments



Additional slides

Numerical experiments

Scheme Error vs Computational Cost ($t = 10.0$)

