

Accelerating Time-Stepping Methods with Surrogate Models

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Goal: solve large-scale initial value problems

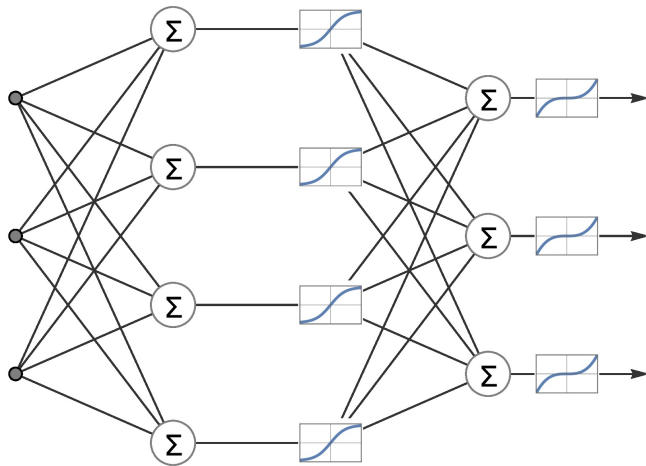
- Consider the initial value problem

$$y' = f(y), \quad y(t_0) = y_0 \in \mathbb{C}^N, \quad t \in [t_0, t_f].$$

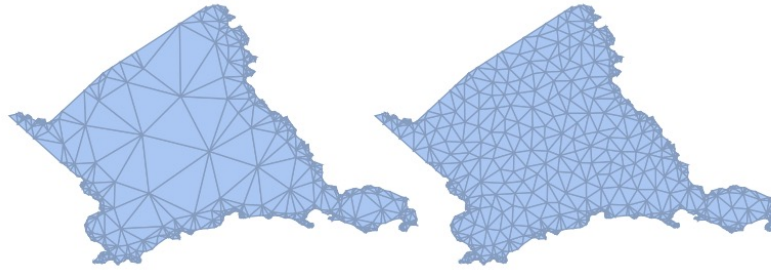
- We will focus on explicit methods for nonstiff problems.
- In scientific applications, the dimension N can be intractably large and evaluations of f prohibitively expensive.
- How can we reduce the number of evaluations of f without sacrificing
 - Accuracy
 - Stability
 - Convergence

What about surrogate models?

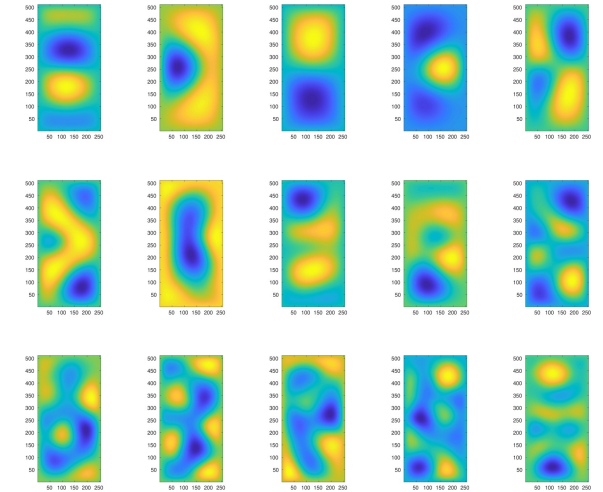
- For many problems, it is possible to produce a cheap but approximate surrogate model.



Machine Learning



Coarser Mesh



Reduced-Order Model

- For complex problems, surrogate models cannot outright replace the full model f .

How can we combine full and surrogate models?

- For convergence, we cannot escape evaluating the full model.
- An ideal hybrid approach would use the surrogate model to substantially reduce evaluations of the full model.
- Surrogate models have been successfully incorporated into optimization algorithms.
- There are some related ideas in the context of time integration
 - Rosenbrock-W methods
 - Coupling a reduced order model and multirate method¹
 - Defect correction
 - Heterogeneous multiscale method²

1. Hachtel, Christoph, et al. "Multirate DAE/ODE-simulation and model order reduction for coupled field-circuit systems." Scientific Computing in Electrical Engineering. Springer, Cham, 2018. 91-100.
2. Abdulle, Assyr, et al. "The heterogeneous multiscale method." Acta Numerica 21 (2012): 1-87.

Defining the surrogate model

- Recall the full model we want to integrate is

$$y' = f(y), \quad y(t) \in \mathbb{C}^N.$$

- The surrogate model is also posed as an ODE:

$$y'_{sur} = f_{sur}(y_{sur}), \quad y_{sur}(t) \in \mathbb{C}^S.$$

- The surrogate model may evolve in a lower-dimensional space: $S < N$.
- Transformations between the full and surrogate spaces are realized by $V, W \in \mathbb{C}^{N \times S}$:

$$y_{sur} = W^* y, \quad y \approx V y_{sur}, \quad W^* V = I_{S \times S}.$$

Surrogate acceleration with multirate methods

- The original, full ODE can be rewritten in the equivalent form

$$y' = V f_{sur}(W^* y) + f(y) - V f_{sur}(W^* y) \in \mathbb{C}^N.$$

- Idea: apply a multirate method to this ODE.
 - The “fast” partition is the surrogate model and is treated with a small timestep.
 - The “slow” partition is the surrogate error and is treated with a large timestep.
- The surrogate model is evaluated often to guide the solution trajectory while the expensive full model is evaluated infrequently to correct for surrogate errors.
- Accuracy, stability, and convergence properties are based on the underlying multirate method.

Which multirate methods should we use?

- With 6 decades of development, there are many options!
- Multirate infinitesimal (MRI) methods have gain traction in recent years.
 - Fast dynamics are evolved by solving ODEs with any consistent integrator.
 - Very flexible
- MRI methods based on Runge-Kutta methods
 - Knoth, Oswald, and Ralf Wolke. "Implicit-explicit Runge-Kutta methods for computing atmospheric reactive flows." *APNUM* (1998)
 - Sandu, Adrian. "A class of multirate infinitesimal GARK methods." *SINUM* (2019)
 - Roberts, Steven, Arash Sarshar, and Adrian Sandu. "Coupled multirate infinitesimal GARK schemes for stiff systems with multiple time scales." *SISC* (2020)
- MRI methods based on linear multistep methods
 - Demirel, Abdullah, et al. "Efficient multiple time-stepping algorithms of higher order." *JCP* (2015)

Multirate Euler method example

- Our multirate ODE is

$$y' = f^{\{f\}}(y) + f^{\{s\}}(y).$$

- Consider the simple multirate infinitesimal method

$$\begin{aligned}v(0) &= y_n, \\v'(\theta) &= f^{\{f\}}(v(\theta)) + f^{\{s\}}(y_n), \\y_{n+1} &= v(H).\end{aligned}$$

- There is one evaluation of $f^{\{s\}}$ per step.
- $f^{\{f\}}$ is evaluated as many times as it takes to integrate v to $\theta = H$.

Multirate Euler method example

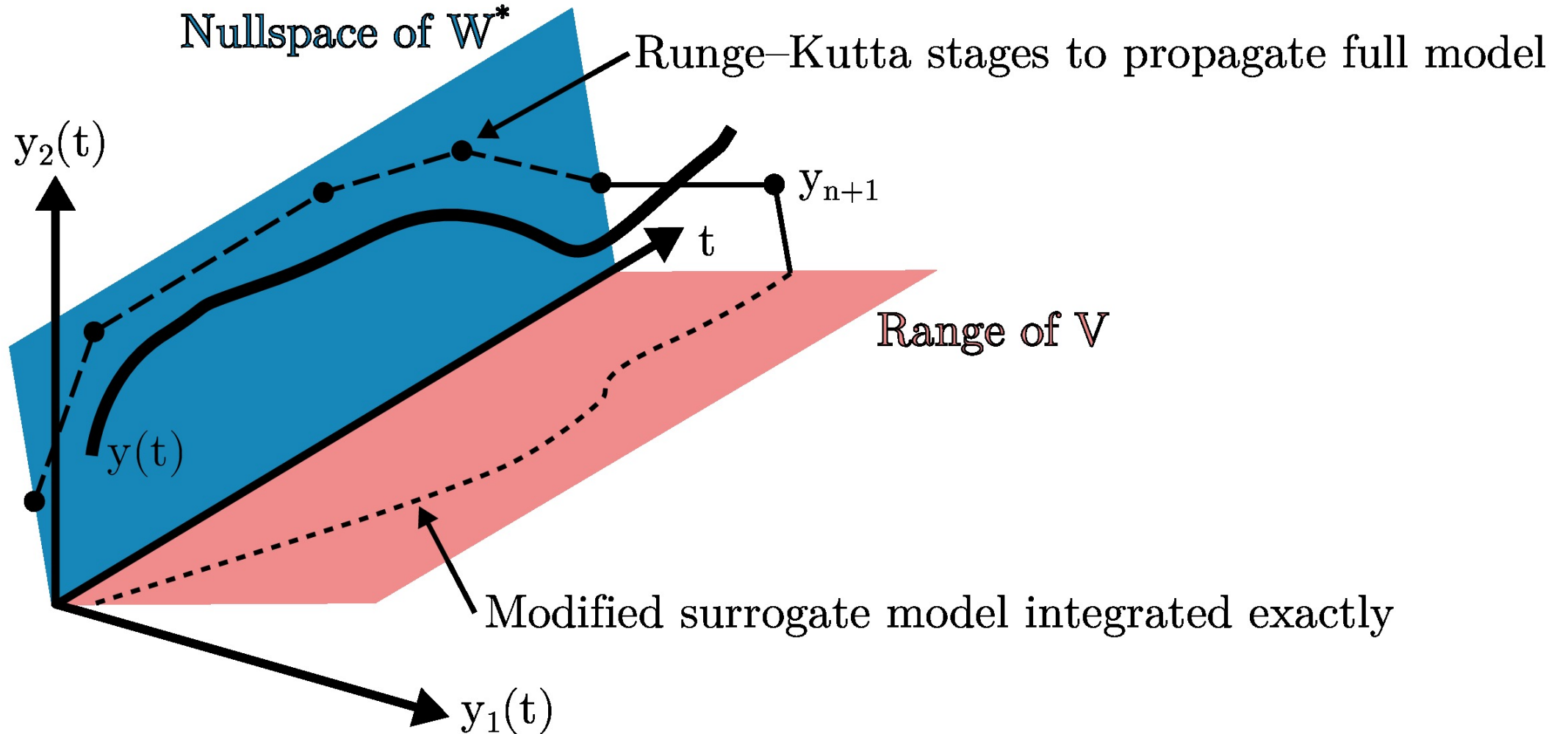
$$y' = Vf_{sur}(W^*y) + f(y) - Vf_{sur}(W^*y)$$

- When we apply the multirate Euler method to our ODE, we arrive at

$$\begin{aligned}z(0) &= W^*y_n, \\z'(\theta) &= f_{sur}(z(\theta)) + W^*f(y_n) - f_{sur}(W^*y_n), \\y_{n+1} &= Vz(H) + (I_{N \times N} - VW^*)(y_n + Hf(y_n)).\end{aligned}$$

- $z(\theta) \in \mathbb{C}^S$ is integrated in the range of V .
- An Euler step is taken in the nullspace of W^* .
- There is one evaluation of the full model per step and many for the surrogate model.

Illustration of the time-stepping approach



$$y' = Vf_{sur}(W^*y) + f(y) - Vf_{sur}(W^*y)$$

- Let's replace multirate Euler with MRI-GARK to achieve higher orders.
- A surrogate model MRI-GARK (SM-MRI-GARK)¹ method is given by

$$\begin{aligned}
 Y_1 &= y_n, \\
 z_i(0) &= W^*Y_i \in \mathbb{C}^S, \\
 z'_i(\theta) &= \Delta c_i^{\{s\}} f_{sur}(z_i(\theta)) + \sum_{j=1}^{i+1} \gamma_{i,j} \left(\frac{\theta}{H} \right) (W^*f(Y_j) - f_{sur}(W^*Y_j)), \\
 Y_{i+1} &= V z_i(H) + (I_{N \times N} - VW^*) \left(Y_i + H \sum_{j=1}^{i+1} \bar{\gamma}_{i,j} f(Y_j) \right), \quad i = 1, \dots, s^{\{s\}}, \\
 y_{n+1} &= Y_{s^{\{s\}}+1}.
 \end{aligned}$$

1. Roberts, Steven, et al. "A Fast Time-Stepping Strategy for Dynamical Systems Equipped with a Surrogate Model." *SIAM Journal on Scientific Computing* 44.3 (2022): A1405-A1427.

$$y' = Vf_{sur}(W^*y) + f(y) - Vf_{sur}(W^*y)$$

- If instead we base our method on SPC-MRI-GARK we have the class of surrogate model SPC-MRI-GARK (SM-SPC-MRI-GARK)¹:

$$Y_i = y_n + H \sum_{j=1}^{s\{s\}} a_{i,j}^{\{s\}} f(Y_j), \quad i = 1, \dots, s\{s\},$$

$$z(0) = W^*y_n \in \mathbb{C}^S,$$

$$z'(\theta) = f_{sur}(z(\theta)) + \sum_{j=1}^{s\{s\}} \gamma_j \left(\frac{\theta}{H} \right) (W^*f(Y_j) - f_{sur}(W^*Y_j)),$$

$$y_{n+1} = V z(H) + (I_{N \times N} - VW^*) \left(y_n + H \sum_{j=1}^{s\{s\}} b_j f(Y_j) \right)$$

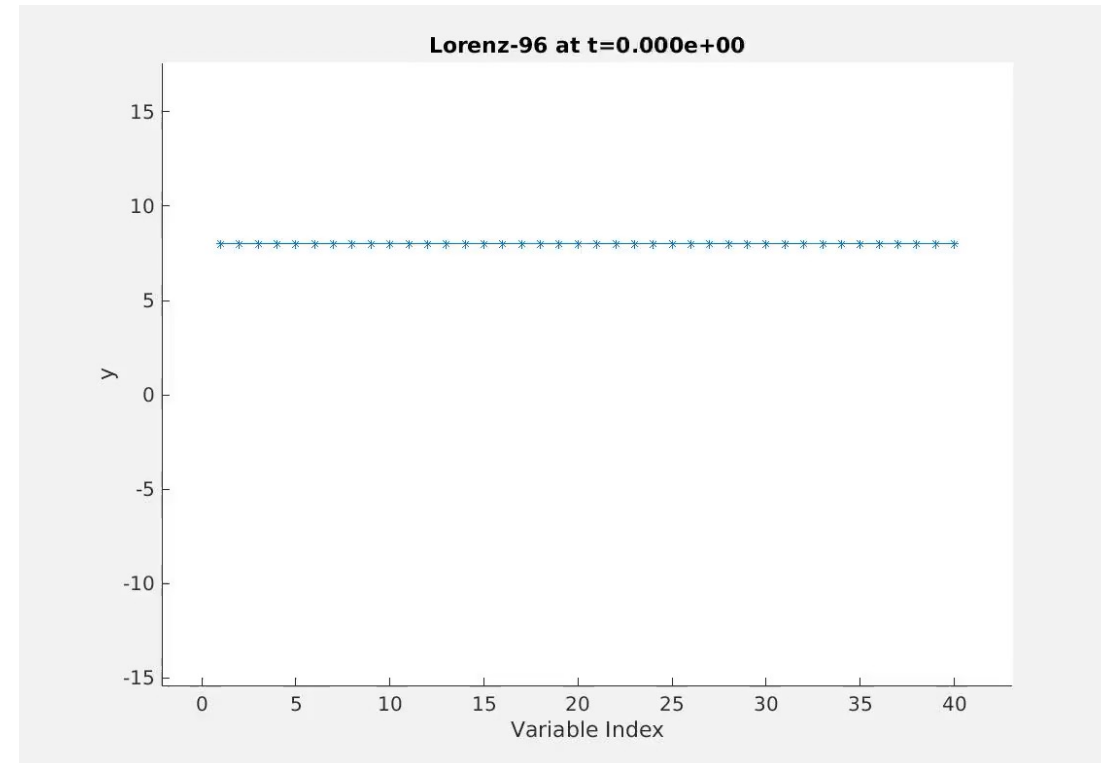
1. Roberts, Steven, et al. "A Fast Time-Stepping Strategy for Dynamical Systems Equipped with a Surrogate Model." *SIAM Journal on Scientific Computing* 44.3 (2022): A1405-A1427.

Numerical experiment: Lorenz '96

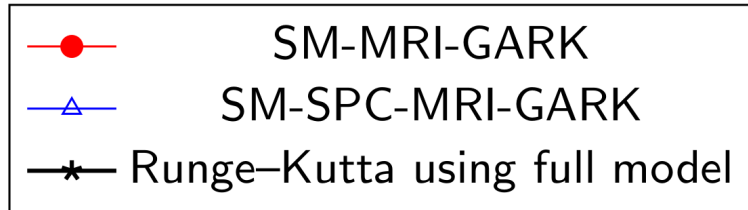
- The Lorenz '96 is a 40 variable ODE

$$\frac{dX_k}{dt} = -X_{k-2}X_{k-1} + X_{k-1}X_{k+1} - X_k + F.$$

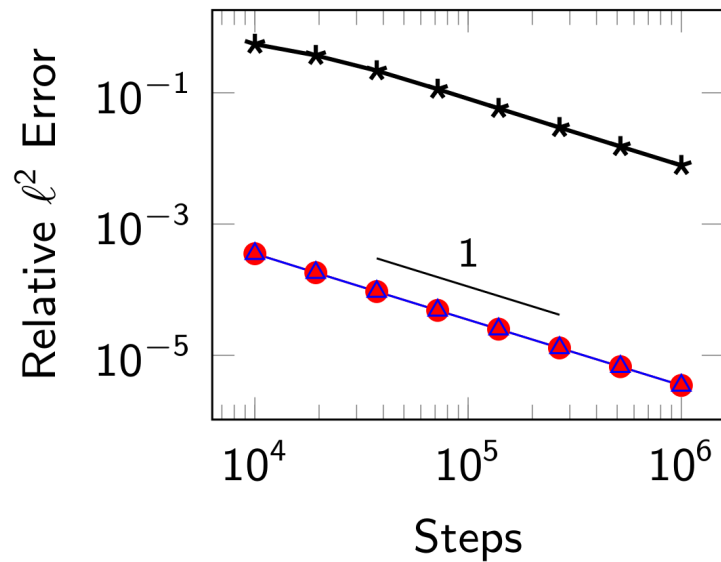
- In an offline phase, 5000 snapshots of the trajectory and its derivative were generated over the timespan $[2, 10]$.
- A 3-layer neural network was trained on the data to approximate the RHS function f .
- The neural network acts as f_{sur} , and $V = W = I_{40 \times 40}$.



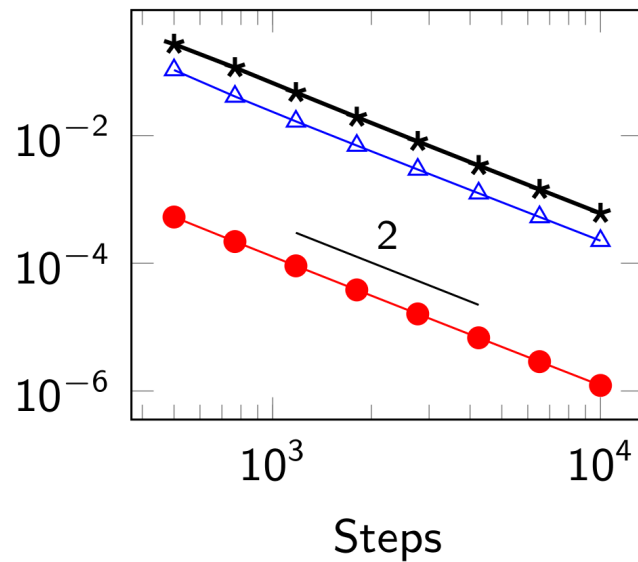
Numerical experiment: Lorenz '96



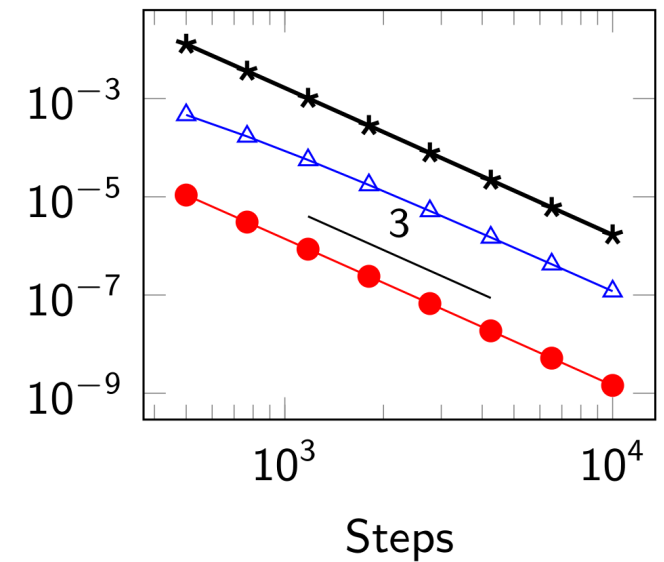
First order Euler



Second order Ralston



Third order Ralston



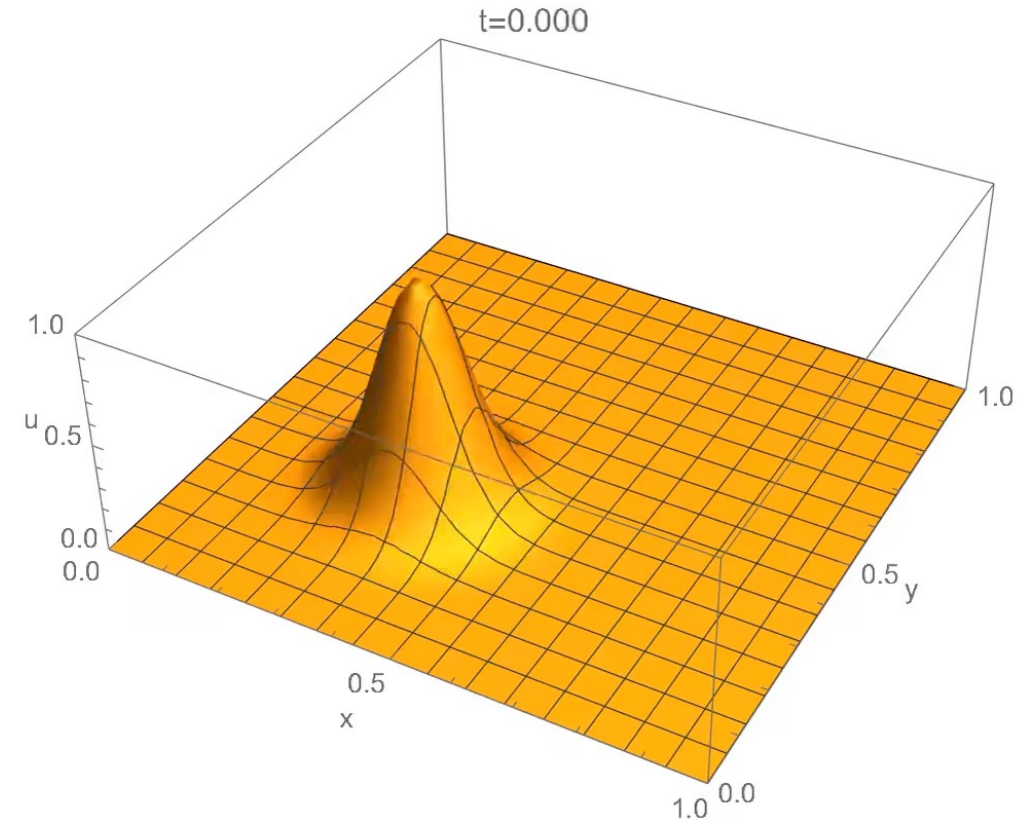
Numerical experiment: DG advection

- Consider the Molenkamp-Crowley problem

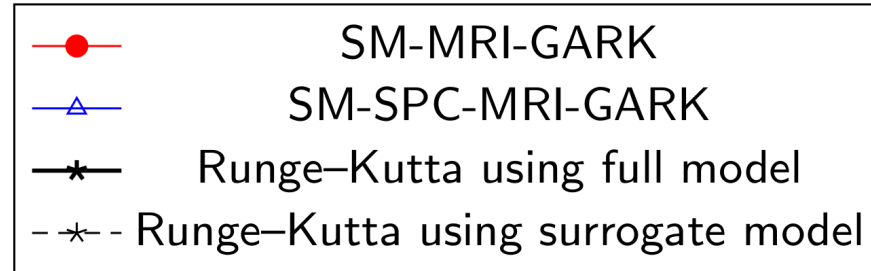
$$\frac{\partial u}{\partial t} + a \cdot \nabla u = 0, \quad \text{on } \Omega = [0,1]^2,$$
$$u = 0, \quad \text{on } \partial\Omega,$$

with the circular wind profile $a(x, y)$.

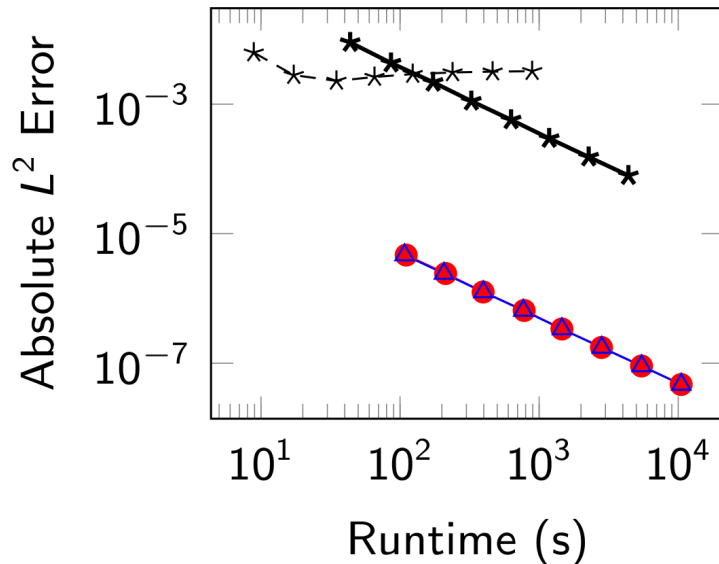
- f corresponds to a discontinuous Galerkin discretization on a 100×100 uniform triangular mesh, while f_{sur} uses a 50×50 mesh.
- V and W^* are sparse interpolation operators.



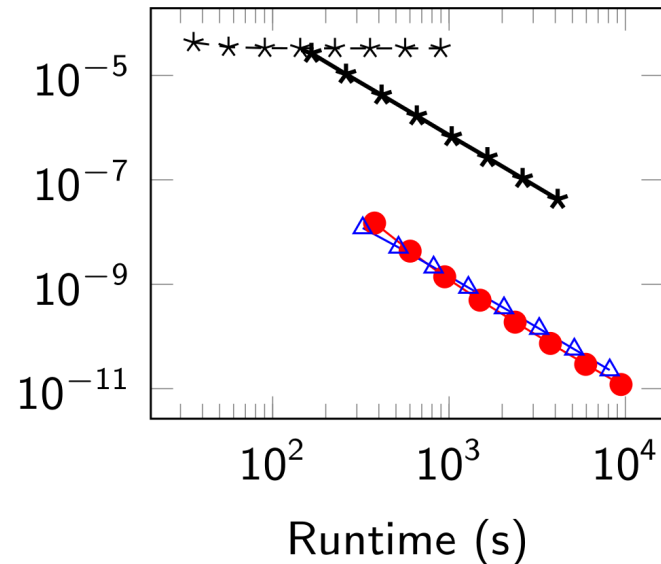
Numerical experiment: DG advection



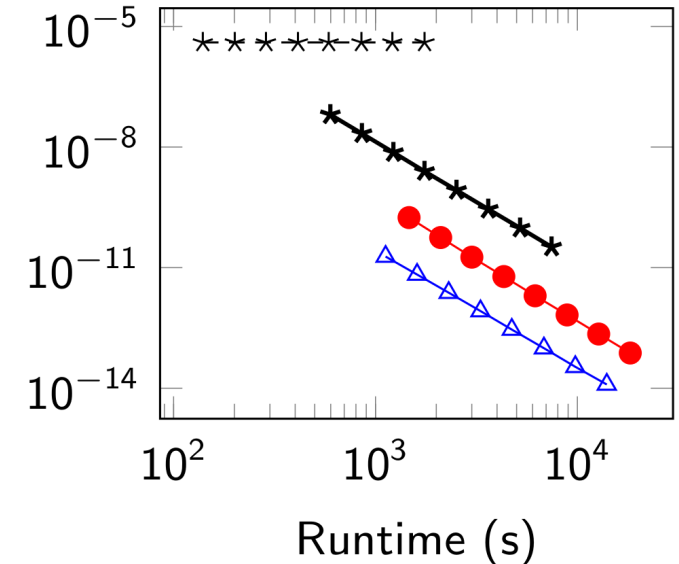
First order Euler



Second order Ralston

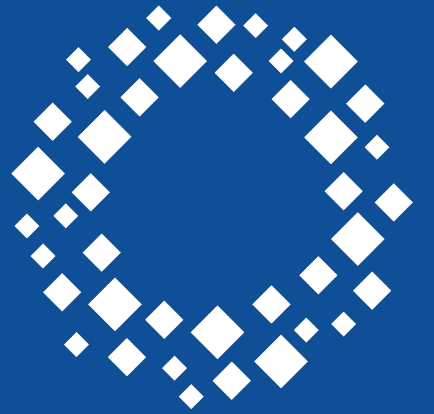


Third order Ralston



Conclusions

- New methods extend traditional Runge-Kutta and linear multistep methods to incorporate information from a surrogate model.
- This work broadens the scope and applicability of multirate methods.
- The quality of the surrogate model does not affect the order of convergence.
- Experiments show large speedups over traditional integrators, especially when V , W^* , and f_{sur} are inexpensive.
- Future work
 - Additional testing of methods based on linear multistep methods
 - Support for surrogate models that are flow maps instead of ODEs



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Questions?

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